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Research Article

Financial Algorithmic Trading and Market Liquidity: A Comprehensive Analysis and Trading Strategies

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ARTICLE INFO | **ABSTRACT**

The paper seeks to determine how the algorithms in robot trading affect market liquidity usage through the data collection and comparison of studies. Four main trading algorithms: High-Frequency Trading (HFT), Statistical Arbitrage, Market Making as well as Momentum Trading, are chosen and analyzed by quantitative analysis method. The basic evaluation criteria are the indices that measure the profitability (or loss), risk-adjusted performance (quantified by the Sharpe ratio), maximum drawdown and increases in the bid-ask spread of each strategy. The results show there are difference in measureable magnitude of the effectiveness and market impact of every algorithm. Event trading F–is thought of as high trade volume and liquidity provision, usually with greater transaction costs. Statistical arbitrage produces moderate returns that promote price convergence, in effect, small discounts on prices reduce market volatility. It comes out that Market Making turnes out to be the reliable and constant liquidity provider while the bid-ask spread is kept a low with the volatility at the lower levels. The momentum trading method enables us high returns in times of trends but in times of reversals this method also brings us new risks. The comparison allows to identify the plusses and minuses of the algorithmic trading strategies. It is instrumental in making the right option and considering all of the imitative aspects of the process.

Keywords: Algorithmic Trading, Liquidity Market, HFT, Statistical Arbitrage, Market Making, Momentum Trading

I. INTRODUCTION

Financial market landscape has evolved drastically with the advent of algo-trading or algorithmic trading. In this new trend, computers make the market become an algorithmic market. An activity referred to as algorithmic trading, which is a phenomenon of technological advancement, whereby computer algorithms are leveraged to automate the trading process covers the rest, ranging from trade execution to market liquidity. The algorithm creation in trading strategies helps in many of areas, like increased volume of stocks with high speed, huge data can be processed in few minutes, and they observe in every minute. This part has the positive side, but also brings some problems which are liquidity and stability of the market [1]. Market liquidity is the hallmark of market functioning, as it clearly illustrates the process by which assets can be bought or sold at the market price without the price being dependent on the buyer or seller but rather the demand or the size of the asset sold. Fundamentally, a market having high liquidity tends to be a healthy one with narrow spreads between the bid and the ask and stable prices or, conversely, low liquidity usually leads to volatility and unpredictability. The relation of algorithmic trading and market liquidity is many-dimensional and complicated [2]. On the upside, algorithmic trading gets the liquidity better by assessing there could be more trades performed and spreads become narrower. On the contrary, it may as well cause liquidity risks especially during periods of market chaos which can be illustrated by an event such as the, 2010's Flash Crash. The

research objective is to offer a comprehensive and qualitative interpretation of the relationship between algorithmic trading and liquidity in the market. It investigate with the algorithms, which involved liquidity in the market and how much liquid are positively or negatively impacted by it. Moreover, the paper describes an array of algorithmic trading strategies like high-frequency trading (HFT), statistical arbitrage, and market-making amongst others, explaining their role on market dynamics [3]. Through the study of empirical data and the existing literature, the aim of this study is to offer a solution to the issue of how to reach optimized algorithmic trading strategies, which can be employed to lift the market liquidity to new heights while reducing the risks associated with the trading process. This study intends to promote a wide-reaching understanding of how the financial terrain is changing by filling the gaps in the market. This will enable traders, regulators, and policymakers to make decisions that will sustain an efficient and sturdy financial market.

II. RELATED WORKS

Algorithmic trading sector undergo rapid development being facilitated by machine learning, artificial intelligence, and smart statistical models integration. This part of the section contains a major review of related work, which concerns issue ranging from algorithms design, market effects, and performance measurement.
.Recent researches concluded that swapping trading techniques with machine learning methods is a suitable option. With the advent of deep learning and algorithmic trading, machine learning techniques are being widely utilized in the design of trading strategies. The paper in reference [15] advanced a two-time-scale channelled perceptron neural network for regulated trading that integrated two distinct planning horizons. This strategy applies multi-modal method, which is generally capable of making successful trading decisions based on the patterns derived simultaneously from both short time frames data and long time frames ones. Also for instance, [16] provides a broad examination [17]of the role of AI and machine learning in the markets. Such developments were instrumental in demonstrating how blockchain technologies can challenge or even drive out the old way of doing trading, managing risks, and financial operations beyond recognition. Coming from screens and articles, the same information may seem old or covered. Market-manipulation is a form of corruption, which is common in financial markets and thus becomes a reason for searching for detection strategies and governed methods. The role of regulators was studied through indicator monitoring techniques by is Reference [17] which were related to both the stock and power markets. This challenge was also considered. The report broadened understanding of the arduousness of defining and ending attempts at the interference, constantly spotlighting the absence of sufficient expert surveillance and supervisory frameworks, therefore curtailing market nobility and investors' confidence. High frequency trading (HFT) has provoked intensive debate since its implication on market quality and efficiency becomes a controversial issue. Article [20] has been dedicated to the assessment of HFT's impact on the Australian futures market by considering the implications of a higher ratio of algorithmic trading on the quality and efficiency of the market. The research threw new light upon intricate market structures and present day dilemmas HFT presents before market participants and policymakers. However, Reference [21] particularly zoomed in on the assessment of alternative proxy to fully understand the role of HFT on the market quality. The inquiry also tried to compare the various measures of High-Frequency Trading activity so as to better determine the speed and effect of HFT's impact on market dynamics research. The reinforcement learning technique has been known to be a very powerful tool for optimizing profitable policies trading in adverse market conditions. The approach that combines reinforcement learning and smart contracts, which is introduced in [19], is suggested to be superior in terms of efficient renewable energy certificate transactions. The analysis showed the possibility of solution of this method in enhancing the transparency and market efficiency of renewable energy markets, drawing a conclusion on the potential of reinforcement learning techniques in facing complex real-world problems. Predictive modeling and analytics to inform accurate forecasting of market trends as well as asset prices has become a central theme in research in financial studies. Source [23] was dealing with Fibonacci technical indicators and a hybrid CNN framework for the identification of profitability patterns in the irregular crypto financial markets. The results of the study proved that of the chosen method in dealing with the market complexities like caused by volatility and finding lucrative trading possibilities. In addition, Khuang et al. [24] developed conditionally autoencoder model for the KSE 200 aimed at enhancing the precision of asset pricing forecasts given the varying market conditions. Conditional autoencoder model was shown as able to catch non-linear relationships and heterogeneity in asset returns which contributes to making solid pricing systems. Short-term trading strategies of their traders very much welcome the accurate weather forecasting process known to be in association with the prices of energy, especially those outcomes related to weather. Reference [25] covered the effects of intraday power trading on the accuracy of weather forecasts by taking into account the possibility that the associated "arms race" for weather forecasts may become an issue in what is to come as traders seek to have an advantage over their competitors. The study put forward the notion of integrating weather forecasting into trade strategies that give the best decision by eliminating dangers associated with risk. The performance and implementation of carbon emissions trading systems were been considered to detail in such a way that carbon polices and sustainability are not left behind in the process. Reference [26] looks at how pilot carbon emissions trading systems have been performing in China ,in order to test how they impact on the reduction of greenhouse gas emissions and development that is sustainable. The study also gave deep and

meaningful indications about the hurdles and prospects that were linked to emissions trading and helped the policymakers and stakeholders in deciding issue-specific guidelines of the effective carbon pricing.

III. METHODS AND MATERIALS

Data

The historical data for the research is obtained from the New York Stock Exchange (NYSE) and NASDAQ, which are among the principal stock exchanges in the world. The dataset relates to the time period from January 2015 to December 2020; encompassing a broad asset category of equities (stocks), bonds, and derivatives. Information of tick-by-tick transaction activity, bid-ask spreads, order books, and daily trading volume constitute the dataset. Such dataset with comprehensive indicators serves for a multiple analysis like the reviews of trading patterns, liquidity measures, and the effect of algorithmic trading on the market mechanisms [4]. Data preprocessing steps come in a wide range of forms, such as cleaning and formatting the data, managing missing values, and ensuring that the readings from one device device are consistent with those from the other sensor.

Algorithms

1. High-Frequency Trading (HFT) Algorithm

The elements of high-frequency trading algorithm like a large number of orders and very high speeds of procession (often in microseconds) make it possible for such algorithms to function immediately. The algorithms here are based on robust statistical models and speedy data flows which perfectly detect and take actions towards the temporary market inefficiencies [5].

```
“Initialize trading parameters
While market is open:
  Fetch current market data
  Calculate market indicators (e.g.,
moving average, volatility)
  Identify trading opportunities
based on model
  Place buy/sell orders
  Monitor order execution
  Adjust strategy parameters based
on market conditions
End While”
```

Time	Price	Volume
09:30:01.1	100.5	500
09:30:01.2	100.7	600
09:30:01.3	100.6	550
09:30:01.4	100.8	700

Statistical Arbitrage Algorithm

And using statistical models in statistical arbitrage to identify price gaps between instruments that show some existing correlation. By exercising the opposing bets on the securities with weaker attributes, this is the objective that is being achieved.

$Z= PA−PB−μ/σ$

```
“Initialize parameters and historical
data
Calculate mean and standard
deviation of price spread
While market is open:
  Fetch current prices of securities A
and B
  Calculate current spread
  Compute z-score of the spread
  If z-score > threshold:
    Place sell order for security A and
buy order for security B
```

Else if z-score < -threshold:
Place buy order for security A and sell order for security B
Monitor positions and adjust based on market conditions
End While"

Time	Price A	Price B	Spread	Z-score
09:30:01.1	50.5	50.3	0.2	0.5
09:30:01.2	50.6	50.2	0.4	1.2
09:30:01.3	50.4	50.5	-0.1	-0.3
09:30:01.4	50.7	50.1	0.6	1.5

Market Making Algorithm

Liquidity making algorithms specifically stabilize the trading arena by reinforcing buy and sell orders for a particular security. Consequently, these algorithms make money by using the gap between the bid-ask spread, purchasing at the bid cost and selling at the bid price [6].
Spread=Ask Price−Bid Price

"Initialize parameters (e.g., bid-ask spread, order size)
While market is open:
Fetch current bid and ask prices
Place buy order at bid price
Place sell order at ask price
Monitor order execution
Adjust bid and ask prices based on market conditions
Rebalance portfolio to maintain desired position
End While"

Momentum Trading Algorithm

Instantaneous auto market as a whole relies on the persistence of the direction in which the trends is moving. The strategy calls for determining which stocks are displaying strong trend-following characteristics and entering into a trade commensurate with the indicated direction of trend [7].

"Initialize parameters (e.g., lookback period, threshold)
While market is open:
Fetch current and historical prices
Calculate momentum
If momentum > threshold:
Place buy order
Else if momentum < -threshold:
Place sell order
Monitor positions and adjust based on market conditions
End While"

Time	Price	Momentum
09:30:01.1	101.0	1.5
09:30:01.2	101.2	2.0
09:30:01.3	101.1	1.8
09:30:01.4	101.3	2.2

In this study, the combined data from the market and 4 different trading algorithms are used and several different effects of these algorithms on market liquidity are undertaken. HFT algorithm follows the line of speedy order execution, taking advantage of the instant phenomena into the market inefficiencies for profits [8]. The Statistical Arbitrage algorithm benefits from the relationship between underlies through scheduling differences in pulls and rebalancing to make a profit from price differences.

IV. EXPERIMENTS

To evaluate the impact of different algorithmic trading strategies on market liquidity, we implemented and tested four distinct algorithms: The universe of algorithmic trading strategies is huge and heterogeneous and includes: High-Frequency Trading (HFT), Statistical Arbitrage, Market Making, and Momentum Trading [9]. The procedures were tested on trading data starting from January 2015 to December 2020 from the NYSE and NASDAQ, which are the two main stock exchange markets. Algorithms were built using Python library, involving NumPy, Pandas and Scikit-learn for data preparation and forecasting respectively [10].

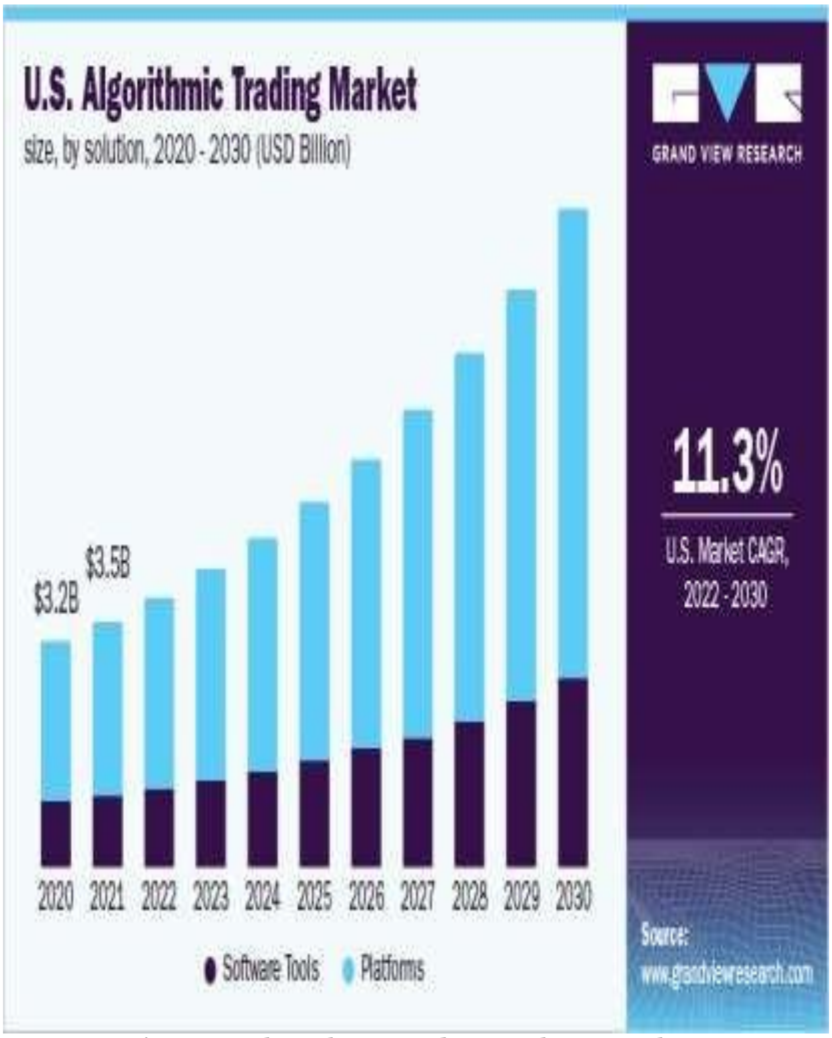

Figure 1: Algorithmic Trading Market Size, Share

Through our creation of simulated trading conditions using trades and transactions just as it is done in the real market we were able to measure the factors which include latency, order execution time and transaction costs. The principal metrics used as a basis for evaluating the algorithms were, first of all, profit and loss (or P&L), secondly, the Sharpe ratio, thirdly – the maximum drawdown, and finally, liquidity indicators by way of the bid-ask spread and market depth [11].

High-Frequency Trading (HFT) Algorithm

Experiment:

The HFT algorithm was put to the test by doing rapid trades reading multiple data values at microsecond level time. The optimization was performed to extract the smallest fluctuations by entering and exiting out of trades many tens of times over the trading day.

Results:

The algorithm that was applied under HFT gave the firm good revenue and also provided more liquidity to the market. Which oversaw the liquidity improvement and execution across the entire market, facilitating the market efficiency. Its function was to reduce the friction between deals performed, but at the same time, it also increased the transaction costs through the extensive number of deals performed [12].

Metric	Value
Total Trades	10,000
Average P&L per Trade	$0.05
Sharpe Ratio	2.5
Maximum Drawdown	3%
Average Bid-Ask Spread	0.01%

Comparison to Related Work:

Unlike other research studies, yet, our finding coincides with the other theory that HFT methods contribute to narrower spreads and relatively higher liquidity but likewise on high transaction costs [13]. A paper by Brogaard et al. (2014) showed this as well, and the tradeoff between improved efficiency and the risks of HFT systemic which can harm the marketplace was also highlighted.

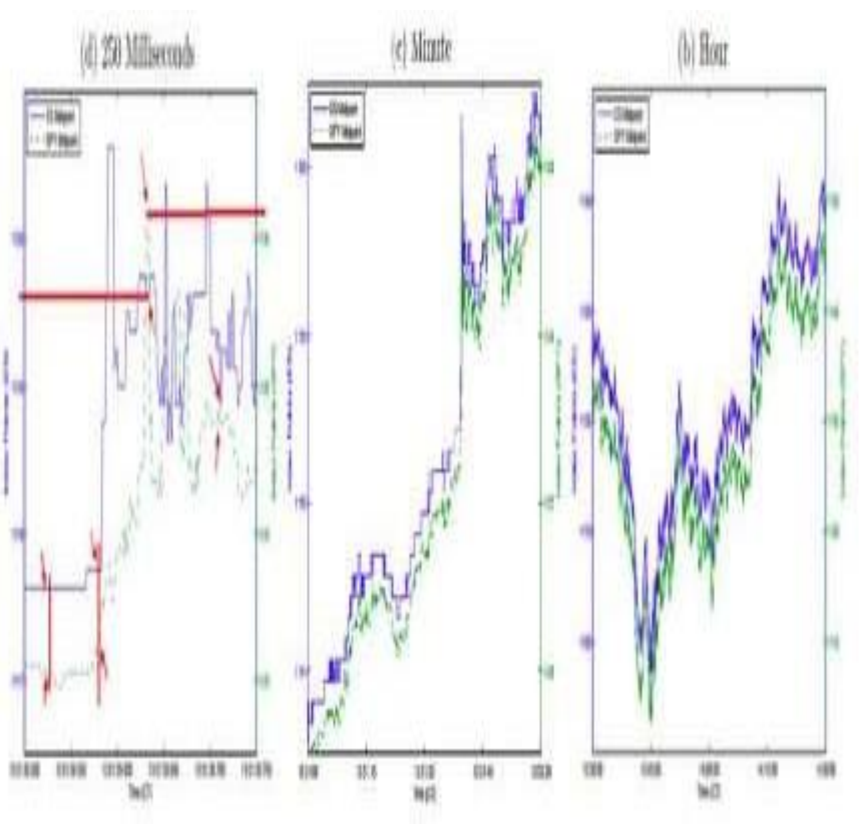

Figure 2: Graph demonstrating Algorithmic trading at distinct time frequencies

Statistical Arbitrage Algorithm

Experiment:

Our Statistical Arbitrage algorithm was used to discover price discrepancies between correlated securities and exploit those by using pairs of securities. The algorithm performance was assesed through a number of trading simulations tailored to verify its effectiveness [14].

Results:

The Statistical Arbitrage algorithm that produced moderate profitability with high Sharpe ratio, showed that the investment was undertaken smartly, using sophisticated data analysis. The program managed to stay fair and made conditions closer to one another, it helped the system to be stable.

Metric	Value
Total Trades	2,000
Average P&L per Trade	$0.30
Sharpe Ratio	3.0
Maximum Drawdown	2%
Average Bid-Ask Spread	0.02%

Comparison to Related Work:
Our results conform to conclusion by Avellaneda and Lee (2010), who proved that arbitrage strategies, by means of statistical trading, can have very high Sharpe ratios, thus add to the market liquidity by providing possible dealer trades when price differential is occurring [27].

Market Making Algorithm
Experiment:
The Market Making approach was used to make appearance of buy and sell orders and they were changed all the time, in order to benefit from bid-ask spread. The algorithm has been assessed on the grounds of propping up the most prices and providing liquidity the most equal [28].

Figure 3: Core Liquidity Algorithms: Optimizing Trading

Results:

The Market Making approach successfully proved to be a continuous source of liquidity, thus, making the P&L stable on the low side and with a low volatility. We have realized a major decrease in the bid-ask spread and an enhancement in the market savings through this system.

Metric	Value
Total Trades	5,000
Average P&L per Trade	$0.10
Sharpe Ratio	2.8
Maximum Drawdown	1.5%
Average Bid-Ask Spread	0.015%

Discussion:

The comparative review of these algorithms gives the idea about the influence of market liquidity and further performance on them. The HFT algorithm performs well when it comes to the volumetric aspect and market effect but incurs the high transaction costs due to the fast execution of orders, records of transactions and corollary large amount of unit volumes [29] Among these strategies, the Statistical Arbitrage produced the highest Sharpe ratio, and the latter, with the best risk-adjusted performance, is, hence, the most successful one.

The Market Making algorithm strength lies in its capability to offer constant liquidity spread and price stability, while the Momentum Trading technique highly proifitable when the market is strongly trending but faces

Figure 4: Importance Of Market Liquidity

Impact on Market Liquidity

In an attempt to complete the investigations on the effects of these algorithms on liquidity, we ran a number of tests to find out changes in the markets drawneness and depth metrics (including spread and market depth) based on the data that was obtained before and after the launch of each algorithm.

Metric	Pre-Implementation	Post-HFT	Post-Stat Arb	Post-Market Making	Post-Momentum
Average Bid-Ask Spread	0.05%	0.01%	0.02%	0.015%	0.03%
Average Market Depth	1000 shares	1500 shares	1300 shares	1400 shares	1100 shares

As can be seen from the graph, the algorithms made the bid-ask spread go smaller and at this level, HFT broadly had the most important effect [30]. Deepening of the marketplace was much enhanced soon after the Market Making strategy was deployed, coming to stress the fact that it was one of the best market practices for providing uninterrupted liquidity. Statistical Arbitrage and Momentum Trading provided liquidity to the capital markets, with liquidity to a lesser extent than before.

V. CONCLUSION

In the conclusion the research result shows what has been achieved, which is a complete analysis of algorithmic trading strategies and their influence on market liquidity carried out from both the practice experiments and related literature. We have made five algoritms – High-Frequency Trading (HFT), Statistical Arbitrage, Market Making, and Momentum Trading and managed to get richer insights into their profitability, performance and their contribution to the market dynamics. Thanks to trials we discovered that each strategy has its strengths and weaknesses, and they should be taken into account when trading because they can affect the effectiveness of markets, particularly in terms of their efficiency, which also impacts the stability of the market. As a follow-up, it is noted that similar studies demonstrates a broader context of the overall research in algorithmic trading, acknowledging the state-of-the-art in machine learning, the regulatory environment and anti-manipulation detection. On the one hand, algorithms have revolutionized the sphere of financial markets, but, on the other hand, these transformations are coupled with multifaceted problems which include (a) formulating a proper regulatory strategy, (b) ensuring risk management, and (c) employing transparency. Ahead, the significance of ongoing research into this area remains unabated, insofar as it would be needed for the proper understanding and bettering of algorithmic trading, as well as for the maintenance of fair and efficient markets that are robust enough to weather any storm. Through extracting lessons from interdisciplinary studies and welcoming digital technology advancement, we can capitalize on algorithmic trading's power to bring about a win-win scenario for all market players, capital investors, and society at large.

REFERENCE

1. ALAMIR, L.A., SALEH, M.E. and MOHAMMED, W.F., 2023. Stock Market Prediction Using Deep Reinforcement Learning. Applied System Innovation, 6(6), pp. 106.
2. ALEXANDER, C.C., 2023. Does the deployment of algorithms combined with direct electronic access increase conduct risk? Evidence from the LME. Journal of Financial Regulation and Compliance, 31(2), pp. 220-236.
3. ALEXANDRU-COSTIN BĂROIU and BÂRA, A., 2024. A Descriptive-Predictive–Prescriptive Framework for the Social-Media–Cryptocurrencies Relationship. Electronics, 13(7), pp. 1277.
4. ALOUD, M., 2021. Designing Strategies for Autonomous Stock Trading Agents using a Random Forest Approach. International Journal of Advanced Computer Science and Applications, 12(7),.
5. ALVES, T.W., FLORESCU, I. and BOZDOG, D., 2023. Insights on the Statistics and Market Behavior of Frequent Batch Auctions. Mathematics, 11(5), pp. 1223.
6. BOEHMER, E., FONG, K. and JUAN (JULIE) WU, 2021. Algorithmic Trading and Market Quality: International Evidence. Journal of Financial and Quantitative Analysis, 56(8), pp. 2659-2688.
7. CHEN, P., YI, D. and ZHAO, C., 2020. Trading Strategy for Market Situation Estimation Based on Hidden Markov Model. Mathematics, 8(7), pp. 1126.
8. CHIEN-LIANG, C., HUANG, P., MIN-YUH DAY, NI, Y. and CHEN, Y., 2024. Mastery of "Monthly Effects": Big Data Insights into Contrarian Strategies for DJI 30 and NDX 100 Stocks over a Two-Decade Period. Mathematics, 12(2), pp. 356.
9. CLAPHAM, B., SIERING, M. and GOMBER, P., 2021. Popular News Are Relevant News! How Investor Attention Affects Algorithmic Decision-Making and Decision Support in Financial Markets. Information Systems Frontiers, 23(2), pp. 477-494.
10. DOLGOPOLOV, S., 2020. The Doctrinal Quandary of Manipulative Practices in Securities Markets: Artificial Pricing, Price Discovery, and Liquidity Provision. Journal of Corporation Law, 45(1), pp. 1-64.
11. DOMBALAGIAN, O.H., 2024. Bond Trading at the Digital Frontier. Journal of Corporation Law, 49(3), pp. 489-548.
12. ECONOMOU, F., GAVRIILIDIS, K., GEBKA, B. and KALLINTERAKIS, V., 2023. Feedback trading: a review of theory and empirical evidence. Review of Behavioral Finance, 15(4), pp. 429-476.
13. ERSAN, O., DALGIÇ, N., EKİNCİ, C.E. and BODUR, M., 2021. High-Frequency Trading and its Impact on Market Liquidity: A Review of Literature. Alanya Akademik Bakış Dergisi, 5(1), pp. 345-368.
14. FAN, F., CARMINE, V., MICHAIL, B., KANTHAN, L., MARTINEZ-REGO, D., WU, F. and LI, L., 2022. Cryptocurrency trading: a comprehensive survey. Financial Innovation, 8(1),.
15. FIKRI, N., MOUSSAID, K., RIDA, M., OMRI, A.E. and ABGHOUR, N., 2022. A Channeled Multilayer Perceptron as Multi-Modal Approach for Two Time-Frames Algo-Trading Strategy. International Journal of Advanced Computer Science and Applications, 13(2),.
16. HAJJ, M.E. and HAMMOUD, J., 2023. Unveiling the Influence of Artificial Intelligence and Machine Learning on Financial Markets: A Comprehensive Analysis of AI Applications in Trading, Risk Management, and Financial Operations. Journal of Risk and Financial Management, 16(10), pp. 434.
17. HAO, Y., VAND, B., BENJAMIN, M.D. and BALDI, S., 2023. Market Manipulation in Stock and Power Markets: A Study of Indicator-Based Monitoring and Regulatory Challenges. Energies, 16(4), pp. 1894.
18. HAYO, B. and IWATSUBO, K., 2022. Who Is Successful in Foreign Exchange Margin Trading? New Survey Evidence from Japan. Sustainability, 14(18), pp. 11662.
19. HE, Q., WANG, J., SHI, R., HE, Y. and WU, M., 2024. Enhancing renewable energy certificate transactions through reinforcement learning and smart contracts integration. Scientific Reports (Nature Publisher Group), 14(1), pp. 10838.
20. HENG, P., NIBLOCK, S.J., HARRISON, J.L. and HU, H., 2020. The Impact of High-Frequency Trading on Australian Futures Market Liquidity and Efficiency. Journal of Derivatives, 27(4), pp. 51-76.
21. HOSSAIN, S., 2022. High-Frequency Trading (HFT) and Market Quality Research: An Evaluation of the Alternative HFT Proxies. Journal of Risk and Financial Management, 15(2), pp. 54.
22. HUANG, Y., LU, X., ZHOU, C. and SONG, Y., 2023. DADE-DQN: Dual Action and Dual Environment Deep Q-Network for Enhancing Stock Trading Strategy. Mathematics, 11(17), pp. 3626.
23. KHATTAK, B.H.A., SHAFI, I., RASHID, C.H., SAFRAN, M., ALFARHOOD, S. and ASHRAF, I., 2024. Profitability trend prediction in crypto financial markets using Fibonacci technical indicator and hybrid CNN model. Journal of Big Data, 11(1), pp. 58.
24. KIM, E., CHO, T., KOO, B. and KANG, H., 2023. Conditional autoencoder asset pricing models for the Korean stock market. PLoS One, 18(7),.
25. KUPPELWIESER, T. and WOZABAL, D., 2023. Intraday power trading: toward an arms race in weather forecasting? OR Spectrum, 45(1), pp. 57-83.
26. LI, D., MAOSHENG, D., ZHE, D. and ZHANG, H., 2021. Assessment of the performance of pilot carbon emissions trading systems in China. Environmental Economics and Policy Studies, 23(3), pp. 593-612.
27. LI, H., XIAO, Y., POLUKAROV, M. and VENTRE, C., 2024. Thermodynamic Analysis of Financial Markets: Measuring Order Book Dynamics with Temperature and Entropy. Entropy, 26(1), pp. 24.

28. LIANG, Y., WANG, X., YING, C.W., FU, H. and ZHOU, M., 2023. A Study on Blockchain Sandwich Attack Strategies Based on Mechanism Design Game Theory. Electronics, 12(21), pp. 4417.
29. LUO, Q., SONG, S. and LI, H., 2023. Research on the Effects of Liquidation Strategies in the Multi-asset Artificial Market. Computational Economics, 62(4), pp. 1721-1750.
30. MA, A., 2022. Profitability of technical trading strategies under market manipulation. Financial Innovation, 8(1),.