

Algorithmic Trading and Market Fairness: An Evaluation of the Efficiency, Inequality and Regulatory Challenges of Automated Financial Markets

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Abstract

Algorithmic trading has transformed modern financial markets by allowing computerized systems to analyze information and execute trades at speeds beyond human capability. This paper investigates the extent to which algorithmic trading enhances or undermines fairness in stock markets. By drawing on academic research, market evidence and regulatory analysis, the paper evaluates algorithmic trading through its effects on price discovery, transaction costs, market access, liquidity and systemic risk. The findings suggest that algorithmic trading substantially improves market efficiency by accelerating price discovery and increasing liquidity. That said, these benefits coexist with structural inequalities arising from unequal access to high-speed infrastructure, proprietary data and sophisticated trading technologies. Events such as the 2010 Flash Crash further demonstrate the potential systemic risks of highly automated markets. The paper concludes that algorithmic trading improves market efficiency but does not necessarily create fairer markets, making effective regulation, technological oversight and stronger governance increasingly important as trading algorithms become more sophisticated.

Keywords: Algorithmic trading; High-frequency trading; Market efficiency; Market fairness; Financial regulation

Introduction

Modern financial markets are no longer controlled by humans but by algorithms that can execute thousands of trades in milliseconds, with accuracy humans struggle to match.

Modern stock markets have evolved significantly due to rapid advancements in technology, computing power and data analysis. Stock markets depended on human traders to execute transactions physically at stock

exchanges. In contrast, modern stock markets are now powered by algorithmic trading, where computer programs execute trades on their own, following a set of instructions and live market data (CFI, 2019). Algorithmic trading accounts for a large share of modern stock market trading because it can execute more trades in less time. The expansion of high-speed internet connections and artificial intelligence has further accelerated this shift to algorithmic trading. As a result, algorithmic trading has become more attractive to stock market users and a central tool many financial professionals rely on. Thus, it consequently has a significant effect on price levels and movements, liquidity and volume in markets worldwide.

While algorithmic trading encourages efficiency, it raises questions regarding fairness in financial markets. Some argue that it benefits markets by improving liquidity, reducing transaction costs and enhancing price discovery. However, others argue that it unfairly benefits large financial institutions, which have access to superior technology and algorithms, while disadvantaging individuals and smaller firms that may not have the same resources. This paper will examine the following research question: **To what extent does algorithmic trading enhance or undermine fairness in stock markets?**

This paper argues that algorithmic trading can improve efficiency in financial markets but can also create structural inequalities and challenge the fairness and equality of financial markets.

What Is Algorithmic Trading And How Does It Work

Algorithmic trading refers to the utilization of computer programs to automate steps required to execute a trade, encompassing data analysis, trading signals and executing the order itself. In a practical situation, it works by transforming a trading strategy into computer code, where the program can accurately and swiftly check market data, including variables like volume, price and certain patterns, and then analyze it using a set of rules before immediately responding by executing the trade if the rules are met (Medium, 2024).

Algorithmic trading did not emerge as a breakthrough technology; it evolved over years of development and refinement. Initially, its rise was heavily influenced by the introduction of digitalized trading in the American markets during the 1970s. A key event that spurred the rise of algorithmic trading was the New York Stock Exchange's introduction of the Designated Order Turnaround system in 1976 (Fabino, 2023). This system, for the first time, allowed orders to be sent and processed digitally. Since then, the use of algorithmic trading has increased rapidly; the percentage of trades carried out by algorithms increased from 10% in 2011 to 50% in 2019 and the global algorithmic trading market was valued at USD 17.0 billion in 2023 and is projected to reach USD 65.2 billion by 2032, growing at a CAGR of 15.9% from 2024 to 2032 (Allied Market Research, 2024).

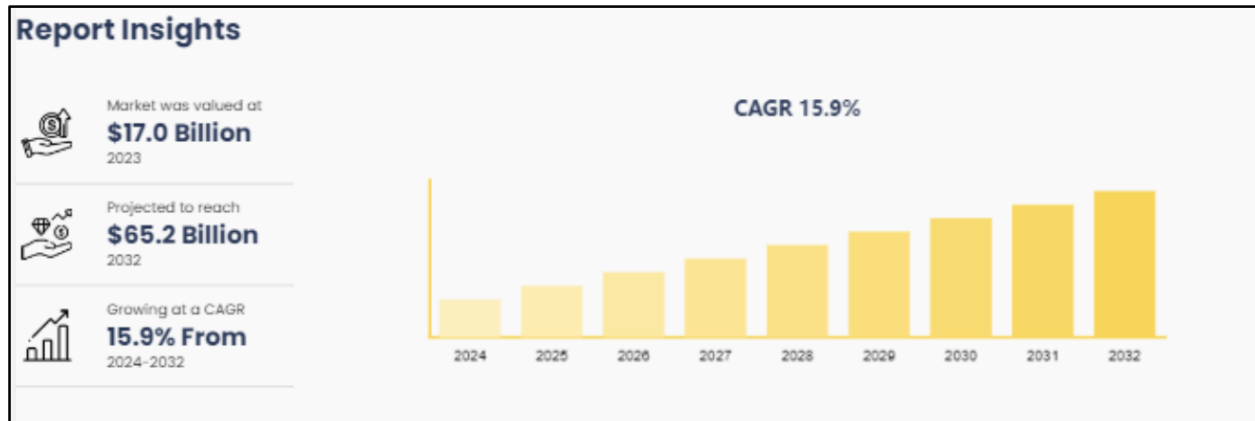


Figure 1: Algorithmic Trading Market CAGR

However, algorithmic trading is not a single tool; it is an umbrella term covering several types of tools that serve different purposes in financial markets. There are three main types of algorithms: execution algorithms, profit-seeking algorithms and high-frequency trading algorithms (Fabino, 2023).

High-frequency trading (HFT) is the most technically demanding and precise form of algorithmic trading. It is highly focused on speed, so much so that firms place their computers geographically closer to exchange servers, a method known as co-location, just so that their trade orders travel the shortest distance to the servers and so that the trade can be executed as fast as possible (Picardo, 2019). HFT has allowed trades to move at extraordinary speeds. A decade ago, firms competed and executed trades in milliseconds; now they execute in microseconds and even nanoseconds, with companies pouring money into undersea cables, dedicated data fields and microwave links to gain a nanosecond edge (Aquilina, Budish and O'Neill, 2021).

Execution algorithms are designed to carry out large trades without moving the market. They do this by breaking large orders into smaller ones, spread out over time or across different trading venues. This type of algorithmic trading is important and especially useful because large orders are hard to manage; executing large trades all at once could increase volatility, and it keeps trades consistent and accurate, which humans can fail at under pressure (Medium, 2024).

Market-making algorithms consistently place buy and sell orders for a security, earning a small profit between the lower buy price and the slightly higher sell price, known as the bid-ask spread, while keeping markets liquid. This type of algorithmic trading heavily relies on the exchange rules on order priority, and interestingly, more than 98.5 of the orders they place are canceled before being completed, which just shows to what extent it relies on order priority rules, and reflects on how precise it is and how rapidly it reacts to the volatile and dynamic conditions of the markets (Shukla, 2015).

Altogether, these different systems and methods of algorithmic trading show that algorithmic trading is not one simple program, but a broad network of technologies. In simple terms, algorithmic trading involves four steps: designing a strategy, connecting the program to a live stock market through an API, allowing the program to place orders, and then analyzing the results to identify any issues with the program (Medium, 2024). Understanding how each of these mechanisms works is necessary before assessing algorithmic trading on balance and whether it makes markets fairer and more efficient, or if it does not or instead does the opposite

Efficiency and Functional Benefits of Algorithmic Trading

One of the most common arguments for algorithmic trading is that it can make markets more efficient. In economics, an efficient market is one where prices quickly and accurately reflect all current information, transactions can be processed and completed smoothly, and trading costs are low. The Efficient Market Hypothesis (EMH), introduced by economist Eugene Fama in 1970, underpins this idea. The hypothesis suggests that a market is informationally efficient when asset prices at any given moment reflect all available information. For example, if a company announces record profits, its share price should react almost immediately as traders incorporate the new information into their buying and selling decisions (Cochrane, 2014). In such a market, traders should not be able to consistently outperform the market using publicly available information, because the information should already be rapidly incorporated into asset prices. Algorithmic trading, which processes information and acts faster than any human trader possibly could, is evidently the practical realization of what the Efficient Market Hypothesis defines as an ideal and efficient market.

Evidently, the most significant way in which algorithmic trading supports market efficiency is through faster and more precise price discovery, which is how a stock price adjusts to new relevant information. According to a 2020 study by Syamala and Wadhwa, stocks listed on the National Stock Exchange of India had more accurate, quicker-reacting prices on days when algorithmic traders were more active, and the opposite when they were less active. Their findings show that algorithmic trading brings more accurate and faster price discovery to the market, as information can be absorbed and acted on faster (Syamala & Wadhwa, 2020). This makes markets more reactive to real-world events. In a practical situation, it means that in the event of a major decision by the central bank, geopolitical news or the announcement of record profits, prices in a market with more algorithmic traders can adjust within milliseconds, rather than minutes, which could mislead or disadvantage regular traders.

Another closely linked aspect is the improved market liquidity that algorithmic trading facilitates. According to a study done by the researchers Hendershott, Jones and Menkveld (2011) on the New York Stock Exchange, found that after the New York Stock Exchange's introduction of automated quote dissemination in 2003,

algorithmic trading narrowed spreads, reduced and improved price informativeness. For investors, narrower bid-ask spreads mean lower trading costs. This matters because even a tiny reduction in spread costs, added up over thousands of trades, can add up, especially for ordinary investors, who cannot negotiate lower costs the way institutions can.

Altogether, the improvements that algorithmic trading brings to markets, including better price efficiency, increased liquidity and lower trading costs, show that there are real, significant benefits of algorithmic trading in markets, as it helps markets to carry out their core function of connecting buyers and sellers at fair prices (Park, 2025). In this context, substantial research across various markets strongly supports algorithmic trading's efficiency benefits.

However, we cannot look only at market efficiency and conclude that algorithmic trading is good for the market, because we also have to evaluate how fair it makes the market for everyone. Although algorithmic trading strategies usually narrow bid-ask spreads and improve liquidity, questions remain about how these benefits are distributed across the market and how accessible they are to everyone (Yan et al., 2022). The efficiency improvements are real and significant, but they are facilitated by systems that require a high investment in technology, infrastructure and data, resources primarily accessible by large institutions. This raises an important distinction: a market can be more efficient on average, but still be unfair in how it treats different participants. It is this tension between the efficiency that algorithmic trading provides and the unfair access through which it is used that drives the argument for whether or not algorithmic trading should be used in financial markets, which the following section will examine in depth

Fairness, Inequality And Market Distortion

A central concern raised by many critics of algorithmic trading is not just how it changes market operations, but how it changes the market in ways that benefit certain participants far more than others. Financial markets have always had gaps and differences in knowledge and resources; however, algorithmic trading widens these gaps in a more fundamental way. The main issue is the unequal access to algorithmic trading technology, for example, HFT depends on high-speed networks, co-located servers and live data feeds, which can often only be organised by large financial institutions like investment banks or hedge funds, creating a kind of gap which retail traders will find difficult to fill, as they would struggle to match the speed or accuracy of HFT (PATHAK, 2025). This also exacerbates problems like information asymmetry in modern markets, as some participants not only know more but can also act on that information before other traders have even received the same data.

Retail investors, in particular, may experience more pronounced liquidity asymmetry and stock price volatility as a result of algorithmic and HFT, raising serious ethical concerns about whom the financial market is being built to serve (Yan et al., 2022). Supporters of algorithmic trading argue that this reflects real investment in innovation and that every industry faces a similar situation, where the firm that invests heavily in better technology deserves to profit from it. Additionally, there is some credibility to this argument: algorithmic trading eliminates emotional bias, executes trades objectively and trades on a set of criteria, which can be viewed as adding fairness to competition (Peng et al., 2024). However, the underlying problem is whether financial markets are a fair and level playing field for all investors, which algorithmic trading challenges because it strongly benefits those who can access and implement the technology. When advantages are entirely dependent on the most expensive and refined technology and infrastructure, which are practically inaccessible to retail investors, regardless of their analytical quality or skill, the financial markets can no longer be considered genuinely equal for all (Liu, 2026).

Furthermore, the risks of algorithmic trading go beyond participant inequality. Because algorithms operate at speeds no human can track in real time, they also amplify volatility in ways that destabilize the entire market. Algorithmic trading widens the gap between what investors know and can do, making stock prices susceptible to sudden and asymmetric fluctuations under extreme market conditions (Liu, Shi and Yi, 2026). An important piece of evidence supporting this claim is the Flash Crash of 6th May 2010.

As seen in Figure 2, on that day, a popular index in the U.S. market, the Dow Jones Industrial Average, fell almost 1000 points, or about 9.2%, in just 36 minutes, one of the most dramatic short-term collapses in market history, before partially recovering (Saigal and AlShelahi, 2019).

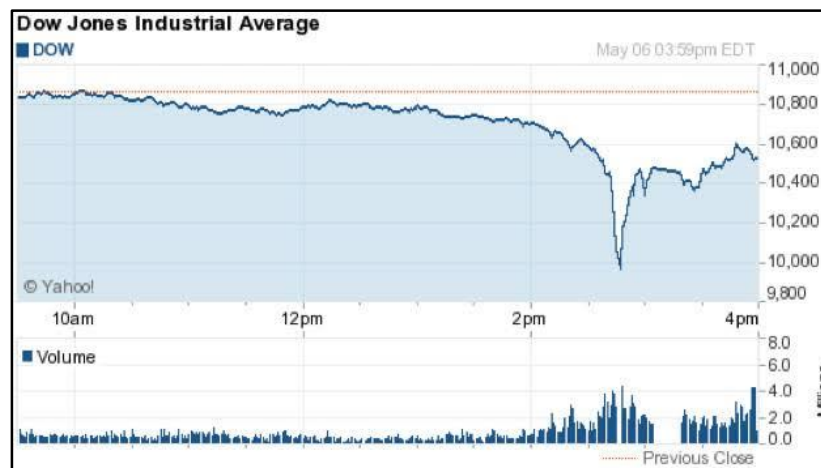


Figure 2: The 2010 Flash Crash

HFT algorithms, designed to exploit small price discrepancies, amplified selling pressure and heightened market volatility as conditions worsened. The SEC and CFTC investigation found that a single large algorithmic trading

sell order in the E-mini S&P 500 futures market, worth approximately \$ 4.1 billion, caused the crash. As this order entered the market, HFT algorithms that had previously supplied liquidity immediately withdrew their orders, removing the support that should have slowed the price decline and instead accelerating it (KIRILENKO et al., 2017).

The Flash Crash isn't just another historical event; it's the strongest evidence that the case for algorithmic trading cannot rest on efficiency alone. It reveals that the same algorithms that appear to stabilize markets under normal conditions can behave in the exact opposite way when conditions become volatile. This raises more questions about whether this was a one-off failure of algorithmic trading or a symptom of a deeper vulnerability within algorithm-driven markets. The speed and interconnectedness of these systems mean small errors can avalanche and spread across markets faster than any human regulator can react.

Regulators must balance the goals of fostering competition and liquidity against fairness and stability in an environment of rapid technological change and significant industry resistance to oversight (Liu, 2026). The efficiency gains described earlier are real and significant, but they also exist only in a system that widens inequality gaps between participants and introduces new forms of systemic risk not present in markets that were primarily human-driven. Whether regulation can successfully address these concerns— and what form it should take is the question this paper will now dive into.

Regulation and the Future of Algorithmic Trading

The risks associated with algorithmic trading do not necessarily mean that the technology itself must be restricted. Instead, regulation increasingly focuses on controlling how algorithms are designed, tested and monitored so their efficiency benefits can be preserved without threatening market fairness or stability. In Europe, MiFID II introduced specific requirements for algorithmic trading, including rigorous testing, transparency and record-keeping requirements intended to prevent algorithms from contributing to disorderly market conditions (KPMG, 2018; Onesti, 2025). Regulatory approaches also include direct safeguards such as circuit breakers, which temporarily halt trading during extreme price movements and provide markets with time to stabilize when automated trading begins to amplify volatility (Lee and Schu, 2021).

However, regulation is becoming increasingly difficult as algorithms themselves become more complex. A review by the UK Financial Conduct Authority (FCA) in 2025 found that although most algorithmic trading firms genuinely understood their regulatory obligations, significant differences remained in the sophistication of their governance and compliance systems. The FCA particularly emphasized the importance of algorithmic testing

under stressed market conditions, pre-and post trade risk controls and effective market abuse surveillance (Carnegie, 2025). This suggests that regulation cannot simply establish rules for trading behavior after trade occurs. Effective oversight increasingly needs to intervene before algorithms enter live markets and continuously monitor their behavior afterward.

This challenge will likely intensify as artificial intelligence and machine learning become more integrated into algorithmic trading. Unlike traditional algorithms that follow relatively fixed instructions, machine learning models can become increasingly adaptive and respond dynamically to changing market conditions (Sekinger, 2026). This may improve efficiency and risk management but could also make trading decisions less transparent and harder for regulators or even firms themselves to explain. Consequently, future regulation is likely to place greater emphasis on algorithmic transparency, human oversight, testing, documentation and clearly defined accountability when automated systems fail (KPMG, 2018).

Conclusion

The rise and implementation of algorithmic trading in stock markets has fundamentally changed how they function, raising an important question: to what extent does algorithmic trading enhance or undermine fairness in stock markets?

The evidence presented in this paper shows that algorithmic trading helps markets achieve higher efficiency. Studies by Reddy and Wadhwa (2020) and Hendershott, Jones and Menkveld (2011) show that algorithmic trading accelerates price discovery, increases market liquidity and reduces transaction costs across major markets. These are real and significant improvements brought about by algorithmic trading that benefit all participants to some extent.

However, while algorithmic trading brings so many benefits to financial markets, it also introduces some major structural inequalities. Access to technologies like high-frequency trading, co-location servers and proprietary data feeds is primarily concentrated among large financial institutions, leaving retail investors disadvantaged and unable to compete fairly and equally, regardless of how good their analysis or judgment is. Notably, the Flash Crash of 2010 revealed systemic risks in algorithm-driven markets: algorithms that usually stabilize markets can, under certain conditions, make them unstable and volatile within minutes, leaving human traders and regulators little time to react or prevent it.

Overall, regulation could reduce some of the risks identified throughout this paper, particularly market instability and abusive algorithmic behavior, but it cannot completely eliminate the structural inequality created by unequal

access to speed, infrastructure and data. Indeed, KPMG (2018) questions whether the continuing competition for lower latency ultimately benefits consumers, since existing market structures inherently reward the fastest participants. Therefore, the future challenge is not choosing between algorithmic trading and regulation, but designing regulation that preserves improvements in liquidity and price discovery while preventing technological superiority from becoming an unlimited competitive advantage. In this sense, effective regulation may determine whether increasingly automated financial markets become merely more efficient or become both more efficient and genuinely fair.

Ultimately, algorithmic trading enhances the operational efficiency of stock markets to a significant extent, but its contribution to fairness remains limited unless regulation can narrow the structural advantages enjoyed by technologically superior market participants.

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