Algorithmic Trading and its Impact on the Market

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***Abstract*— Institutional investors currently use algorithmic trading as one of the most popular and developing trading strategies on the Indian stock market. It is a form of trading where systems are programmed with predetermined rules and instructions to execute transactions at a high rate of speed and accuracy that is hard for human traders to achieve manually. Many retail traders and market regulators have opposed algorithmic trading because of its quick execution. Although algorithmic trading has taken a battering for unintended volatility and blocking market quality by adding large volume at specific levels in accordance with their system or strategy, the evidence relevant to its drawbacks has not yet been established. This paper moves in the right way by supporting algorithmic trading and giving it the credit it deserves for raising market quality. This study analyses the National Stock Exchange's (NSE) stock market to directly identify algorithmic trading. It then aims to identify the primary benefits of algorithmic trading and express the rationale behind its expansion not just in India but also on the international market.**

***Keywords*— Algorithmic trading, Trading Strategies, Computer based trading, Institutional investors.**

I. INTRODUCTION

The rules of conventional broking have changed as a result of algorithmic trading. Trading software must be properly understood by traders in order for them to implement and backtest their strategies while also remaining competitive on exchanges where large volumes are being transacted using complex algorithms. Utilizing cutting-edge technology for stock exchange trading is known as algorithmic trading. Trading entails creating pre-established rules in order to execute the deal to reap results quickly, something a human trader could not do manually.

Because there is little need for a human trader to be involved in this kind of system, decisions are made quickly and precisely. Because of this, the algorithm is able to profit from any market chances well before a trader can even recognise them. It is merely a technique for lowering the price, impact on the market, and risk of slippages. Pension funds, investment banks, hedge funds, and mutual funds frequently use it because these institutional traders must place big volume orders in markets where the size cannot be supported in its entirety at once and must be divided into smaller portions. Over the past few of years, its popularity has grown gradually.

The technical requirements for algorithmic trading are as follows

- Python programming skills, paid programmers, or pre-made trading software are required to programme the necessary trading strategy.
- Fast network connectivity and availability of top-notch trading platforms are required for order placement.
- Access to market data streams via a reputable broker, which the algorithm will watch for opportunities to enter or exit a transaction.
- Before a strategy is implemented on live markets, it should be possible to backtest it to gain insight into its fundamental metrics, such as drawdown, the sharpe ratio, the average risk-to-reward ratio, etc.
- Depending on how intricate the algorithm is that has been implemented rules are, historical data is available for backtesting.

II. RELATED WORK

According to Hendershott and Riordan (2018), algorithmic trading uses cheap liquidity (i.e., when the spread is small) and supplies expensive liquidity. They contend that algorithmic trading systems are more likely to execute trades when spreads are narrow because they are less inclined to place additional buy/sell orders or even to cancel existing ones.

Wu and Siwasarit (2019) propose the Order Imbalance (OI) indicator as a metric to identify price discovery in emerging markets, and they also indicate the non-spontaneous creation of market efficiency. According to the authors' findings, one may anticipate that the order to trade ratio will go down when spreads are bigger and up when spreads are narrow.

According to studies, order expectancy activities are connected to High Frequency Trading firms. Hirschey (2013) discovers that high-frequency traders' aggressive selling behaviours are typically followed by those of non-high-frequency traders, and the trend lasts for up to 10 minutes. The author comes to the conclusion that the occurrence was caused by high-frequency traders' order anticipation tactics.

According to Breckenfelder's (2013) analysis of the NASDAQ OMXS 30 index, the competition among HFT firms leads to an increase in trades that use more liquidity as indicated by the Amihud illiquidity ratio, which depletes the market's liquidity.

According to Brogaard, Hendershott, and Riordan (2014a), aggressive high-frequency traders prefer to trade in the direction of long-term trends rather than against them, which increases overall pricing efficiency.

In three foreign exchange markets—the euro-dollar, dollar-yen, and euro-yen—algorithmic trading is linked to improved price efficiency, as determined by the frequency of triangle arbitrage possibilities and the autocorrelation of highfrequency returns, according to Chaboud et al. (2014).

Using data from 30 stocks from the NASDAQ-OMX Stockholm, Hagströmer and Nordén (2013) find evidence that market-making HFT actions lower short-term volatility (measured by one-minute midpoint quote changes).

According to Boehmer, Fong, and Wu's (2015) global survey of 42 stock 11 markets, short-term volatility (as determined by standardised intraday price ranges) grows as algorithmic trading activity intensifies. Additionally, the authors point out that the rise in volatility cannot be linked to quicker price discovery or algorithmic traders' propensity for trading in unpredictable markets.

According to studies, order anticipation activities are linked to HFT enterprises. Hirschey (2013) discovers that non-high-frequency traders typically follow the aggressive selling activity of high-frequency traders, and the trend lasts for up to five minutes. The author comes to the conclusion that order anticipation tactics used by high-frequency traders are to blame for the phenomena. The E-mini S&P 500 futures market is another place where high-frequency traders may use order anticipation tactics, according to Clark-Joseph (2013).

III. METHODOLOGY

Five-step of implementing algorithmic trading strategies:

A. Choose the genre/strategies paradigm.

The paradigm for the strategy is chosen as the first phase. It can be an execution-based, hedging, market-making, arbitrage-based, or alpha-generating approach. Let's use pair trading as an example of statistical arbitrage that is both market neutral (Beta neutral) and produces alpha, or profits regardless of market volatility.

B. Decide on statistical significance

You can select the specific equities you want to trade using a visual correlation or the market outlook (in the case of pair trading strategy). Verify the statistical significance of the approach for the chosen equities. Check for co-integration of the chosen pairs, for instance, in the case of pair trading.

C. Create a trading model

Now, programme the logic that will serve as the basis for ones strategy's buy/sell signals. When trading pairs, look for "mean reversion"; compute the pair's spread's z-score; and generate buy/sell signals when you anticipate a mean reversion. The "Stop Loss" and "Profit Taking" conditions should be chosen.

D. Hitting or quoting technique

Determining whether the tactic will be "quoting" or "hitting" is crucial. The degree to which your plan will be aggressive or passive is largely determined by your execution approach.

E. Optimisation & Backtesting

Back-testing the technique serves as a vital tool for estimating the proposed hypothesis' performance based on past evidence. If performance data and backtest results support the hypothesis, a strategy is said to be good. As a result, it's crucial to select historical data that has enough data points. In order to cover a variety of market circumstances, this will produce a sufficient number of sample trades (at least 100 trades) (bullish, bearish etc.). Make careful to account for brokerage and slippage fees as well. While backtesting, you might still need to make some approximations to get more realistic results. For instance, it can be challenging to determine when you get a fill while backtesting quotation tactics. Therefore, it is customary to presume that the positions are filled at the price of the most recent deal.

IV. RESULTS

Table 1 Comparison Algo Trading In Indian Stock Market

The Benefits of Algorithmic Trading				
	Frequency	Percent	Valid Percent	Cumulative Percent
Less Room for Error	18	36.0	36.0	36.0
While Trading, It Separates Significant and Irrelevant Factors.	14	28.0	28.0	64.0

Determines The Ideal Market and Time for Trading.	14	28.0	28.0	92.0
Trading Is Made Possible on A Variety of Markets.	4	8.0	8.0	100.0

According to Table 1, algorithmic trading is preferred in the stock market because it decreases the possibility of error because everything is carried out in accordance with set procedures and no psychological factors can influence hasty decisions. Nearly 36% of those surveyed selected this choice. Less room for error exists in algorithmic trading because instructions are delivered based on mathematical models. Thus, all orders will be placed in accordance with the pre-established guidelines, preventing mistakes that could lead to significant losses.

Algorithmic trading reduces market noise since it just follows the data that it receives as input and places orders based entirely on this data. When trading manually, it's possible to be swayed by the media and any tips you may pick up on the street.

The right timing must be present for algorithmic trading to be helpful in trading. Based on the rules that are fed into the system, it also chooses the optimal market to trade on.

The capability of running numerous strategies simultaneously is the primary and most crucial justification for use in the future. Keeping track of more than three to four methods manually isn't possible, however algorithmic trading enables traders to use as many strategies as their capital will support.

Table 2 Comparison of Algorithms in Stock Market in India

Statistics, Descriptive			
	N	Mean	Std. Deviation
Execution Reliability	50	4.66	.479
Being Able to Back Test	50	4.64	.485
Speed and Secrecy	50	4.64	.485
Price Increases	50	4.62	.530
% Commissions	50	4.62	.530
Meets Pre-Trade Expectations	50	4.60	.606

Table 2 shows that the consistency of execution is the main advantage of using algorithmic trading. This is because orders are carried out in milliseconds, and soon nanoseconds, thanks to advances in technology.

The use of previous data for back-testing algorithmic trading is another benefit. One can use this to increase confidence in their system and determine its profitability.

Another benefit of algorithmic trading is understanding the changes in price. Applications for algorithmic trading are readily available, and numerous trading firms offer software solutions for algorithmic trading. They receive technical charts from these software programmes that depict market price changes. This makes it possible for the investor to comprehend the market's movement.

Based on a mean score of 4.60, algorithmic trading enables customization, pre-trade estimate matching, and software programme ease of use.

One of the key advantages of algorithmic trading is that it does away with the influence of psychological barriers on one's decision-making. The trader does not need to become scared or greedy because the execution of orders is based on prearranged instructions based on mathematical models.

V. ADVANTAGES

Some of the proposed benefits of the Algorithmic Trading are envisioned as follows:

A. Lower Prices

Since algorithms are more economical for low-maintenance trades, sales desk headcounts have changed and been reduced as a result. One key advance in reducing trading costs is the ability to send orders to exchanges electronically without going via brokers. Automation has also improved back-office tasks and post-trade services like clearing and settlement.

B. Enables Better Share Pricing and Liquidity

Broker-dealers frequently utilise algorithms to match buy and sell orders without disclosing quotes. Broker Algorithms in a sense enable increased liquidity, price on shares for clients, and larger commissions to brokers by limiting information leakage and accepting both the bid and offer sides of a trade.

C. An Algorithm Can Analyse and Respond to News More Quickly Than a Human Trader.

For instance, an algorithm could notify a trader whenever information on business X is released and if the stock of that firm increases or decreases in value by, say, 1% over the course of five minutes. For instance, clients can leverage live news content from Reuters News Scope Real-time product to power automated trading and react to market-moving events as they happen. To aid automated trading, each news item is electronically "meta-tagged" to identify industries, specific businesses, stories, or certain pieces of data.

D. To Keep an Eye on Risk Situations and Act Quickly When Necessary

Algorithms can automatically hedge a position if a parameter like Value-at-Risk (VaR) is surpassed by using real-time analytics to continuously recalculate VaR.

E. Address Issues with Regulatory Compliance

It is crucial to follow the law, yet doing so is becoming more difficult due to increasingly strict restrictions. Future businesses will increasingly use cutting-edge algorithmic trading technology to address concerns with regulatory compliance.

F. Automated Monitoring

To check for tendencies of misuse in algo trading, regulators could automate surveillance. However, the absence of experienced personnel, adequate IT resources, and the restricted availability of automated surveillance tools for algo trades make supervision technically difficult.

G. Better Price Offered with Little Impact on the Market

The majority of algorithms (which fall under the category of execution algorithms) must offer the best execution pricing for clients placing significant market orders. To lessen the impact of a large transaction on the market, execution algorithms split large orders into smaller orders.

VI. CONCLUSION

One can see algorithmic trading as the future of stock market trading method. For traders managing high volumes and different strategies, it is advantageous. Retail traders, however, cannot afford the cost of running an algorithm, and it is even more difficult for them to quit or enter using a similar approach despite the fact that the algorithm is considerably faster and more accurate. Similar to how SEBI has controlled these trading activities, adequate measures should be made to ensure that they are beneficial to all classes of investors and that, to avoid inequality, trading can be carried out concurrently and at the same time wherever the traders are.

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