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An Overview on Long Short-Term Memory (LSTM)-Based Prediction Model for Stock Market Volatility

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Abstract
Algorithmic trading has revolutionized stock markets, introducing rapid decision-making processes driven by automated systems. Its influence on market dynamics, particularly volatility, has been a subject of intense interest and debate among financial experts and researchers, with a focus on the growing prevalence of algorithmic trading and its potential impact on market stability. This study aims to review related research works that predict the impact of algorithmic trading on stock market volatility using machine learning algorithms. The methodology employed encompassed a comprehensive review of a conceptual framework, empirical review, theoretical review and identifying the gaps within the concept of using machine learning algorithms for the prediction of stock market volatility. The findings of this study provide insight to researchers, investors, traders, and financial institutions such as banks, asset management firms, and hedge funds, for enhancing their risk management practices and also regulators and policymakers to identify models used for predictions.

Keywords: Stock Markets, Machine Learning Algorithms, Prediction, Conceptual Framework, Empirical Review

Introduction

The advent of algorithmic trading has revolutionized the financial markets by automating the trading process, it has increased the speed and efficiency of transactions and has allowed for more complex strategies to be implemented (Chaboud et al., 2014). However, the effect of algorithmic trading on stock market instability is an area of ongoing debate. Algorithmic trading, also known as algo-trading, uses complex algorithms to automate trading decisions (Skrimon, 2023). These algorithms Examine market information, pinpoint potential trades, and swiftly carry out transactions at high speed. (Hendershott & Riordan, 2011). While this has escalated liquidity and improved price efficiency, it has also been associated with increased market volatility (Kirilenko et al., 2017). Market Volatility refers to the pace at which the value of an asset fluctuates, either rising or falling, over a given range of returns. (De Silva et al., 2017). Volatility is a statistical measure of dispersion and is often used as a risk indicator in financial markets. High volatility often signifies financial instability and poses a higher risk to investors.

In recent years, there have been several instances where algorithmic trading was suspected to have caused sudden and extreme market volatility. Consider the Flash Crash, which occurred in May 2010, during which the Dow Jones Industrial Average plummeted by around 1000 points before swiftly recovering those losses within minutes was attributed to algorithmic trading (Kirilenko et al., 2017). Despite the fact that several studies partake in studying the connection between algo-trading and share market volatility, the existing literature presents mixed findings. Previously conducted studies indicate that algorithmic trading can enhance market liquidity and reduce volatility by efficiently matching buyers and sellers (Brian et al., 2021). However, other research indicates that algorithmic trading can lead to increased volatility, mostly during era of market stress or when algorithmic strategies are prone to herding behavior (Budish et al, 2015; Brogaard et al, 2017). Given these concerns, there is a pressing need for models that can predict the effect of algorithmic trading on share market instability. Such models could potentially help in devising strategies to mitigate the adverse effects of algo-trading on market volatility.

The accrued benefit of this review will provide more inside into predictions of market volatility, aiding investors and policymakers in their decision-making processes, and it will enhance the understanding of the effects of algorithmic trading on financial markets. This could lead to the development of more effective trading algorithms and regulatory policies, ultimately contributing to more stable and efficient financial markets. Understanding the connection between algorithmic trading and share market instability is a crucial aspect of this research. Algorithmic trading has the potential to influence stock market volatility through its impact on market liquidity, trading patterns, and reaction speed. This section explores the existing literature and empirical evidence regarding the association between algo-trade and share market fluctuation.

Conceptual Framework

Algorithmic trading, occasionally refers to as automated or systematic trading, has appeared dominant force in monetary markets. It makes use of sophisticated computer system programs to carry out trading commands with speed and efficiency. This section provides an overview of algorithmic trading, its evolution, key components, and its significance in modern financial markets.

Algorithmic Trading

Algorithmic trading, occasionally shortened to algo-trading or automated trading, has emerged as a dominant force in monetary markets, fundamentally transforming the landscape of trading and investment approaches. Automated trading involves the use of sophisticated programs to execute trading orders at high speed and frequency. These sets of rules are written to analyze market records, recognize interchange opportunities, and to automatically perform trades guided by established principles and strategies. The algorithms are often driven by mathematical models, technical indicators, and statistical arbitrage techniques to make well-informed and data-driven decisions. As technology and computing power have advanced, algorithmic trading has gained immense popularity and prevalence across numerous financial marketplaces and asset classes (Joiner, 2022).

One of the primary drivers of algorithmic trading's popularity is its ability to deliver enhanced fluidity and market competence. The subset of algo-trading, High-frequency trading (HFT), is essential for supplying liquidity to financial markets by swiftly matching buy and sell orders. HFT firms leverage advanced algorithms and co-location services to reduce latency and execute trades within microseconds. This liquidity provision contributes to narrower bid-ask spreads, diminishing interchange expenses for investors and enhancing general market fluidness (Menkveld, 2013).

Moreover, algorithmic trading has significantly impacted market microstructure. The rise of electronic trading platforms has eased the seamless execution of algorithmic strategies, enabling traders to access multiple markets simultaneously. This development has led to increased market fragmentation and the proliferation of substitute interchange venues. These changes have presented new challenges and opportunities for regulators to ensure fair and orderly markets (Biais et al., 2018).

The use of algorithmic trading has also expanded beyond traditional equities and now encompasses a wide range of financial instruments, including futures, options, foreign exchange, and cryptocurrencies. Algorithmic trading strategies are often tailored to suit the specific characteristics of each asset class, leveraging diverse data sources and market dynamics to optimize trading performance (Corbet et al, 2020). Critics of algorithmic trading have elevated alarms about its potential effect on market firmness and of "flash crash" risk. May 6, 2010 flash crash, remains a notable incident, during which the Dow Jones Industrial Average experienced a sudden and drastic decline, followed by a rapid recovery. Algorithmic trading's speed and interconnectedness can amplify market movements and create cascading effects, especially during periods of high volatility (Kirilenko et al., 2017).

Regulators worldwide have responded to these concerns by implementing measures to monitor and regulate algorithmic trading practices. Regulatory bodies, comprising the United States, SEC and European Securities Authority, introduced rules surrounding market access, circuit breakers, and pre-trade risk controls to mitigate potential dangers connected to algo-trading (Hendershott & Riordan, 2013).

Despite the concerns, algorithmic trading has become an integral part of financial markets, offering benefits such as increased efficiency, improved liquidity, and enhanced market accessibility. The use of algorithmic trading is expected to continue growing as technology advances and financial markets further embrace automation and digitization (Hasbrouck & Saar, 2013). In conclusion, algorithmic trading has revolutionized financial markets, transforming the way trading is conducted and impacting market dynamics significantly. Its role in providing liquidity, optimizing trading strategies, and shaping market microstructure has been substantial. While regulators continue to address potential risks, the growth and widespread adoption of algorithmic trading underscore its significance in modern finance, where data-driven decision-making and automation are essential components of successful trading strategies.

Stock Market

A stock market is a public marketplace for trading shares, which are ownership stakes in publicly listed companies. Stock exchanges facilitate the buying and selling of these shares (Biswal et al, 2023). In another study, share market was defined as numerous exchanges that exist for trading shares of publicly held companies. These financial dealings take place within formal exchanges and over-the-counter (OTC) markets, each governed by distinct regulations. (Chen, 2023). Stock Market has several significances, it offers a significant avenue for companies to raise capital (Rik et al., 2006). When a company becomes publicly traded via an initial public offering (IPO), it releases shares that are traded on the stock exchange. By selling these shares to investors, the company receives capital that can be used for enlargement, exploration and development, loan repayment, and other tactical investments. Furthermore, the stock market serves as a platform for capital accumulation and allocation, playing a crucial role in the global economy (Mantravadi et al., 2023). In another study, the stock market is reported to be a key player in the efficient distribution and redistribution of national income, as well as in financing the investment activity of enterprises (Meena & Banyal, 2023).

Stock Market Volatility

Stock market volatility refers to the extent of variation around a security's average return, typically calculated using the standard deviation. Stock market instability is commonly measured using statistical indicators such as the standard deviation of daily or intraday price changes. A higher standard deviation indicates greater price variability and, consequently, higher market volatility. Volatility can be both short-term and long-term, influenced by various factors ranging from economic events to market sentiment. Macroeconomic factors, such as GDP growth, interest rates, inflation, and unemployment, significantly impact stock market volatility (Hewamana et al., 2022). Economic indicators and major events, such as changes in financial policy, can influence investor sentiment and trigger volatility. Investor sentiment, whether positive or negative, holds significant influence in shaping market volatility, leading to rapid shifts in stock prices as investors react emotionally to news and events (Hsu et al., 2021). Secondly, Political uncertainty and geopolitical tensions can also create volatility spikes in financial markets. Events such as elections or international conflicts can lead to risk-off sentiments among investors. Additionally, one of the key factors influencing stock market volatility is liquidity. Low liquidity, especially during times of stress or market turmoil, can exacerbate price swings and increase volatility (Zhang et al., 2021). In addition, financial crises can also have an intense influence on share market instability. The 2023 global financial crisis is a prominent example of how systemic risks can lead to heightened volatility across financial markets (Global Risks Report, 2023). The growth of algo-trading and HFT has introduced an additional dimension of volatility to financial markets. Rapid and automated trading activities can amplify price movements and increase intraday volatility (Cartea et al., 2015).

Market structure and regulatory changes can affect stock market volatility, market regulators throughout the world have adopted measures such as circuit breakers to mitigate excessive volatility and protect market stability (Broussard et al., 2022). Stock market volatility is a critical factor in monetary markets, impacting investors, traders, and the broader economy. Comprehending the determinants of share market instability is essential for danger prevention, portfolio allocation, and financial decision-making. Economic indicators, market sentiment, corporate performance, geopolitical events, liquidity, technological advancements, and regulatory changes all contribute to stock market volatility. As financial markets continue to evolve and face new challenges, researchers and market participants must continually assess and analyze the determinants of stock market volatility to navigate the complexities of modern finance.

Deep Bidirectional Recurrent Neural Network

A subfield of machine learning, Deep learning, emerged as a powerful and versatile approach that has revolutionized various industries, including finance. With its capability to process and analyze huge dimensions of complex data, deep learning has found extensive applications in financial markets, offering valuable insights and predictive capabilities. Deep learning is utilizing artificial neural networks to match the human brain's neural connections and learning processes. These networks consist of multiple layers of interconnected neurons, enabling them to learn hierarchical representations of data. By means of an approach called backpropagation, neural networks update their weights to minimize prediction errors, allowing them to uncover intricate patterns and relationships within the data. One fundamental aspect of deep learning are its capability to manage high-dimensional and unstructured data, making it particularly well-suited for the complexities of financial datasets. In finance, deep learning has shown promising applications across a wide range of tasks, including financial forecasting, risk assessment, algorithmic trading, credit scoring, fraud detection, and sentiment analysis. Researchers and financial institutions have increasingly turned to deep learning techniques to extract meaningful information from vast amounts of financial data and to make more informed and data-driven decisions. For instance, in financial forecasting, deep learning models have been employed to predict stock prices, exchange rates, and other market indicators (Shi et al., 2022).

Risk assessment is another crucial area in finance where deep learning has proven its effectiveness. Deep learning models such as Recurrent Neural Networks, LSTMs, and CNNs have been proven to beat traditional machine learning models in credit risk assessment (Shi et al., 2022). Algorithmic trading has been profoundly impacted by deep learning, with financial institutions leveraging neural networks to develop sophisticated trading strategies. Deep learning algorithms, such as deep neural networks (DNNs), offer several advantages in algorithmic trading. DNNs can handle complex and large datasets, allowing more precise predictions and better managerial decisions in trading strategies (Yimeng, 2020). Furthermore, deep learning techniques have proven invaluable in credit scoring, where the models can examine massive volumes of customer records to assess creditworthiness and default probabilities. Studies have shown that deep learning-based credit scoring models outperform traditional scoring methods, enabling lenders to make more accurate credit decisions (Tai & Huyen, 2019).

Impact of Algo-trading on Share Market Instability

The rise of algo-trade has transformed the landscape of financial markets, introducing new dynamics and complexities. Algorithmic trading is the application of computerized programs in trading to automate the execution of trading strategies. In recent decades, the prevalence of algorithmic trading has amplified significantly, this shift has prompted researchers and market participants to examine its impact on stock market volatility. Boehmer et al. (2021) found that algorithmic trading enhances market liquidity and informational efficiency, though it also contributes to short-term volatility. Additionally, their research shows that algorithmic trading reduces execution shortfalls for buy-side institutional investors. Notably, algorithmic trading can increase short-term volatility due to its rapid execution and response to market conditions. Hendershott and Riordan (2011) found that algorithmic trading contributes to higher intraday volatility, especially during periods of market stress and news events. However, it is essential to note that intraday volatility does not necessarily reflect the overall impact on long-term stock market volatility.

Additionally, algorithmic trading is often associated with liquidity provision in monetary markets. In this paper, the authors investigate the effect of Algorithmic Interchange competence on market value dimensions, including fluidity, instability, and price detection measures, researchers utilized tick-by-tick data for orders and trades timestamped at a microsecond level. The study measured algorithmic trading efficiency using 1/OTR and found that higher OTR values were associated with reduced liquidity, increased volatility, and diminished price discovery in the market. Therefore, this study suggests that automated trading competence has a significant effect on the share market (Dubey et al., 2021). Different algorithmic trading strategies may have varying effects on stock market volatility. For example, aggressive high-frequency trading strategies, such as market-making and liquidity-taking algorithms, have been associated with short-term price movements and increased intraday volatility (Biais et al., 2011).

In contrast, passive algorithmic strategies, like liquidity-providing algorithms, can contribute to price stabilization and reduced intraday volatility. Another area of research explores the coexistence of algorithmic and non-algorithmic traders in the market and how their interactions influence volatility. The adoption of regulations, such as circuit breakers and position limits, can act as safeguards against excessive volatility and market manipulation (Li & Zhang, 2021). Moreover, market design features, such as order types and trade execution rules, can affect the conduct of algorithmic traders and their influence on volatility. In conclusion, previous studies on the effect of automated trading on stock market instability have provided valuable insights into the complex relationship between these two factors. Algorithmic trading has undoubtedly altered the dynamics of financial markets, influencing intraday volatility, liquidity provision, and the behaviour of different market participants. The coexistence of algorithmic and non-algorithmic traders further contributes to the complexity of market dynamics and their impact on volatility. While algorithmic trading can increase short-term volatility, it can also contribute to liquidity provision and price stabilization during normal market conditions.

The influence algo-trading has on share market instability is context-dependent and influenced by various factors, including trading strategies, market structure, and regulatory considerations. As financial markets continue to evolve, ongoing research and empirical studies are crucial for developing a comprehensive understanding of the implications of algorithmic trading on share market instability. By gaining deeper insights into these dynamics, market participants and regulators can develop more effective strategies to manage volatility and enhance market stability.

Impact of Algorithmic Trading on Market Liquidity

Several researches have been carried out on the influence of algo trade on market liquidity and its subsequent effect on stock market volatility. Algorithmic trading, by providing continuous liquidity and tighter bid-ask spreads, has been found to improve market liquidity (Frino et al., 2021). Improved liquidity can contribute to lower transaction costs and reduced price impact, which in turn may help mitigate stock market volatility. However, the relationship between algorithmic trading and liquidity is complex. While algorithmic trading can enhance liquidity during normal market conditions, it may also contribute to sudden liquidity shortages during times of market stress, leading to increased volatility (Menkveld, 2013; Budish et al., 2015). The speed and volume of algorithmic trading activities can exacerbate market movements, amplifying volatility during periods of market turbulence.

Trading Patterns and Volatility

The trading patterns associated with algorithmic trading can also impact stock market volatility. High-frequency trading (HFT), a subcategory of automated trading categorized by ultra-fast execution speeds and high trading volumes, has received particular attention in the literature. HFT strategies, such as market-making and liquidity provision, aim to profit from short-term price discrepancies and exploit fleeting market inefficiencies. Empirical studies have found mixed signals regarding impact of HFT on stock marketplace instability. Some findings suggest that HFT contributes to lower volatility by narrowing spreads and enhancing price efficiency (Biais et al., 2011; Menkveld, 2013). On the other hand, other studies argue that HFT can increase volatility through its amplification of market movements and the potential for herding behaviour among high-frequency traders (Budish et al, 2015; Brogaard et al., 2017).

Reaction Speed and Volatility

Algorithmic trading's ability to react swiftly to new information and execute trades within milliseconds can affect stock market volatility. Rapid execution speeds enable algorithmic traders to capitalize on market-moving events and exploit short-lived opportunities. However, this speed can also contribute to the amplification of price movements, particularly in highly correlated markets or during periods of market instability. Studies have shown that algorithmic trading can lead to increased volatility during intraday periods, such as the opening and closing auctions, where algorithmic traders tend to be more active (Bollen, 2011; Chaboud et al, 2014). The high-speed and automatic nature of algorithmic trading can result in intensified price fluctuations and higher trading volumes, potentially contributing to short-term volatility spikes.

Theoretical Framework

Accurate prediction of stock market fluctuation is vital for stockholders, traders, and policymakers to provide insight and manage risk. Over time, several models and approaches have been developed to forecast stock market volatility. This section provides an overview of some of the existing models used for predicting stock market volatility.

ARCH/GARCH Models

Volatility has been modelled and forecasted using the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models extensively. Introduced by Engle (1982), ARCH models incorporate lagged squared error components, which allow for time-varying volatility. Bollerslev (1986) created GARCH models, which are an extension of ARCH models that include lagged squared errors and lagged conditional variances.

The phenomenon of volatility clustering, which is frequently observed in financial time series data and is characterized by periods of high volatility followed by periods of even higher volatility, is captured by these models. Many financial markets have seen the application of ARCH/GARCH models, which have demonstrated encouraging results in forecasting stock market volatility (Andersen et al, 2003; Bollerslev et al., 2008).

Option Implied Volatility Models

Option prices contain valuable information about market participants' prospects of forthcoming volatility. Option implied volatility models utilize the prices of options to estimate the anticipated fluctuations in the base asset's value. The most commonly used option implied volatility model is the Black-Scholes model (Black & Scholes, 1973), which provides an implied volatility measure based on option prices and other inputs.

Option implied volatility models are particularly useful for short-term volatility forecasting, as they incorporate the market's sentiment and expectations. These models have been employed in various studies to predict stock market volatility. For instance, Choi et al. (2010) utilized implied volatility from options to forecast future stock market volatility and found that these measures provided significant predictive power. Similarly, Fleming and Kirby (2011) examined the predictive ability of implied volatility for future market returns and volatility, demonstrating that implied volatility contains information not fully captured by historical volatility models.

Machine Learning Models

Machine learning methods have become increasingly popular in recent times due to their capability to capture intricate patterns and nonlinear correlations within data. Several machine learning models have been applied to predict stock market volatility. Some commonly used machine learning algorithms for volatility forecasting include the like of Support Vector Machines (SVM), Random Forests, and Neural Networks. Machine learning models have been successfully employed to forecast future volatility in monetary markets, including stock market volatility. These models utilize historical price and volume data, as well as other relevant financial and economic variables, to predict future volatility. Machine learning models have shown promising results and have been successful in capturing dynamic and nonlinear patterns in stock market volatility (Tsantekidis et al., 2017; Henrique et al., 2019).

The existing works on the effect of algo-trading on share market instability has provided valuable insights into this complex relationship. However, there are still some prominent gaps in the study that warrant further examination. Firstly, while several studies have examined the short-term intraday volatility effects of algorithmic trading, there is a need for more research on its long-term impact on market stability (Chang & Chou, 2022). Long-term volatility patterns and their association with algorithmic trading strategies remain relatively unexplored. Understanding how algorithmic trading influences market stability over extended periods can provide valuable insights for risk management and policy formulation. Secondly, another crucial gap in the literature is the limited exploration of systemic risk and contagion effects arising from algorithmic trading activities. The interconnectivity of financial markets and the rapid transmission of information among algorithmic traders may lead to the propagation of shocks and market contagion. Investigating the potential for algorithmic trading to contribute to systemic risk can help regulators design effective measures to address such risks. Thirdly, there is a need for more comprehensive research on the impact of algorithmic trading on different asset classes and across various market conditions. Existing studies have predominantly focused on equity markets, leaving other asset classes, such as commodities and foreign exchange, underexplored.

Additionally, algorithmic trading's impact during market crises and periods of extreme volatility requires further investigation to understand its role in amplifying or mitigating market turbulence. Fourthly, research on the behaviour of algorithmic traders during stress events is limited. Examining how algorithmic trading strategies adapt to changing market conditions and contribute to volatility dynamics during stress events can offer critical insights into their role in market stability and resilience. Furthermore, while some studies have explored the coexistence of algorithmic and non-algorithmic traders, more in-depth analysis is needed to understand the interactions and potential conflicts between these two groups. Additionally, the influence of market microstructure factors, such as order flow, trading volume, and bid-ask spreads, on the relationship between algorithmic trading and volatility warrants further investigation. Lastly, research on the impact of regulatory policies on algorithmic trading and its effects on market volatility is relatively scarce. Understanding how regulatory changes, such as circuit breakers and trading halts, influence algorithmic trading behaviour and volatility patterns can guide policymakers in formulating effective regulations to maintain market stability and integrity.

Table 2.1: Further Gap Analysis

Authors	Issues	Design solutions and findings	Gap Analysis
Tsantekidis et al. (2017)	Application of machine learning models in capturing stock market volatility patterns	Machine learning models, such as Support Vector Machines (SVM), Random Forests, and Neural Networks, have shown promising results in capturing dynamic and nonlinear patterns in stock market volatility	Further research could explore the development of ensemble models that combine multiple machine learning algorithms for improved stock market volatility predictions.
Brogaard et al. (2017)	Influence of HFT on stock market volatility	HFT can increase volatility through its amplification of market movements and potential herding behaviour among high-frequency traders	Future studies could investigate the impact of different types of HFT strategies on volatility and the underlying mechanisms driving herding behaviour among high-frequency traders.
Dubey et al. (2021)	Algorithmic trading efficiency and its impact on market quality	They use the Order-to-Trade Ratio (OTR) and devise 1/OTR as a measure of algorithmic trading efficiency. The study confirms that OTR impacts liquidity, volatility, and price discovery.	The authors note that their study does not consider the impact of other market participants, such as institutional investors, on market quality.
Fataliyev et al (2021)	Stock Market Analysis:	Machine learning methods such as ARIMA, SVM, ANN, RF, and hybrid models have been implemented to incorporate textual data and stock data features in stock market prediction.	The first area is the development of more advanced feature representation techniques for textual data in stock market prediction. This includes exploring deep learning algorithms for better feature engineering and representation.

Conclusion

In this study, we embarked on to review of the impact of algorithmic trading on stock market volatility, aiming to identify the gap in predictive models utilizing machine learning algorithms. The methodology employed encompassed a comprehensive review of a conceptual framework, empirical review, and theoretical review and identified the gaps within the concept of using machine learning algorithms for the prediction of stock market volatility. The findings of this study provide insight to researchers, investors, traders, and financial institutions such as banks, asset management firms, and hedge funds, for enhancing their risk management practices and also regulators and policymakers to identify models used for predictions.

Recommendation

Given the unavailability of real algorithmic trading data, our recommendation emphasizes the imperative of securing authentic data sources to further fortify the accuracy and applicability of predictive models in understanding market dynamics.

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