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Trading and Financial Engineering Algorithms on Stock Market Volatility: A Log-Return Model and GARCH (1, 1)-M

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Abstract: This study examines the effects of algorithmic trading and financial engineering strategies on stock market volatility in Indonesia, as well as how their interaction influences price stability. A quantitative approach is employed using volatility estimation through the GARCH (1, 1)-M model and dynamic panel regression based on the Generalized Method of Moments (GMM). The data were obtained from 40 LQ45 stocks with daily frequency throughout 2024, using indicators of algorithmic trading intensity (order-to-trade ratio) and financial engineering (derivatives contract volume). The results show that both algorithmic trading and financial engineering have a positive and significant impact on market volatility. Furthermore, their interaction amplifies volatility, indicating that the integration of trading technologies and financial innovations creates additional pressure on price stability. Theoretically, these findings reinforce the concept of feedback volatility and the endogeneity of risk in the dynamics of modern markets. From a practical perspective, the results highlight the need to strengthen microstructural risk monitoring systems and to design adaptive regulatory policies to address the complexity arising from the interaction between technology and derivatives in capital markets. This study opens avenues for further research on behavioral dimensions, algorithmic regulation, and systemic risks in an increasingly digital and globally integrated market ecosystem.

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INTRODUCTION

In recent decades, the global stock market has undergone a fundamental transformation as rapid advances in information technology, financial computing, and automation of trading systems (Machkour & Abriane, 2020). One of the most prominent manifestations of this transformation is the emergence of algorithmic trading – an automated trading method that uses mathematical algorithms to determine the time, price, and volume of transactions in almost instantaneous time (Addy et al., 2024). At the same time, financial engineering is evolving as an interdisciplinary field that combines applied mathematics, statistics, and financial theory to design derivative instruments as well as complex risk management strategies (Jena et al., 2023).

In the context of an increasingly automated market, stock price volatility is a major issue for investors, regulators, and policy makers. One of the approaches used to measure volatility is logarithmic returns (Miskolczi, 2017), which are additive in time and symmetrical to price changes; $r_t = \ln\frac{P_t}{P_{t-1}}$ where r_t is the logarithmic return at time t, Pt is the closing price of the stock at time t and Pt-1 is the previous closing price. This logarithmic return is the main input in volatility models such as Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) which are the basis for financial engineering-based market dynamics analysis (Kashyap, 2023).

On the other hand, strategies designed through financial engineering, such as optimal portfolios, risk-free arbitrage, and Black-Scholes-based pricing, also involve partial derivatives, exponential functions, and stochastic models (Nuugulu et al., 2023) – all of which are mathematically based. For example, in the Black-Scholes model, where the option price depends on the cumulative normal distribution function of the asset's price log-return: $C = S_0N(d_1) - Xe^{-rt}N(d_2)$ where d1 and d2 are respectively a function of $\ln(\frac{S_0}{X})$ which shows the importance of logarithms in the basic structure of modern financial models. The interaction between trading algorithms and financial engineering strategies not only predicts price movements, but also triggers automatic reactions to market changes in real-time (Lin, 2017). This raises an important question: does the integration of the two strengthen market stability or create additional volatility?

Theoretically, the use of algorithmic trading can increase price efficiency and lower transaction costs such as bid-ask spreads by utilizing directional changes (Adegboye et al., 2023). But in practice, the high frequency and volume of algorithmic transactions can trigger a spike in volatility, especially when multiple algorithms respond to the same market signals simultaneously (Arnoldi, 2016; Bao et al., 2022; Yadav, 2015). On the other hand, financial engineering techniques such as delta-hedging in options can also magnify buying or selling pressure when small changes in the price of the underlying asset demand a significant adjustment of the portfolio's position (Borovkova & Schmeck, 2017; J. Fan et al., 2016; Svirschi, 2012). A flash crash, which is characterized by extreme spikes in logarithmic return variance, $Var(r_t) = E[(rt - \mu)^2]$ – where r_t is the logarithmic return, and μ is the expected value of the return – often associated with the dominance of algorithms and derivatives in modern market ecosystems (Gasparin & Schinckus, 2022; McGroarty et al., 2019; Wehrli & Sornette, 2022a). Therefore, it is important to understand whether the use of algorithmic trading and financial engineering strategies has a simultaneous effect on the increase or decrease in market volatility.

This study aims to answer this question with a quantitative approach based on log-return models and dynamic volatility estimation techniques using GARCH (1, 1)-M. According to (Dwarika et al., 2021) the GARCH model that incorporates variance (or standard deviation) into the mean equation. This means that returns are not only influenced by ordinary factors, but also by risk (volatility). The number (1, 1) indicates an order or lag in the variance equation: 1 lag for the previous squared error (ARCH term), 1 lag for the previous variance (GARCH term). So GARCH (1, 1)-M is GARCH-in-mean with the variance model GARCH (1, 1). By analyzing the interaction of two advanced financial approaches within a modern statistical framework, the study contributes to an understanding of the complexity of the stock market that is increasingly controlled by machines, data, and algorithms.

LITERATURE REVIEW AND HYPOTHESES

The advent of algorithmic trading has been one of the important innovations that reinforces the basic assumptions of the Efficient Market Hyphotesis (EMH) developed by Fama (1970). According to Copeland & Friedman (1987), Fama developed this theory because he believed that stock prices reflect fair value based on publicly and unpublicly available information. In this framework, no investor can consistently make abnormal profits because the information is already fully reflected in the market price. At the time, this was seen as an ideal condition, as stock trading was still done manually on the stock exchange floor, without the help of computers or automated trading systems as it is today, and the dissemination of information did not take place in real-time and tended to be monopolized by large institutional investors. This is acknowledged by itself that Efficient Market Theory was developed as a normative framework, not descriptive (Fama, 1970) – a situation where the market should work under ideal conditions, not how the market actually works at that time. According to EMH, stock prices in the market reflect all available information quickly and accurately. In the era of automated modern markets, algorithmic trading acts as a technological medium that accelerates the process of reflecting that information into prices (Yadav, 2015).

Algorithmic trading is the process of using mathematical algorithms and computer software to automatically execute sell or buy orders in the financial markets (Cohen, 2022). This algorithm follows a pre-programmed set of rules based on time, price, volume, or other market signals without any direct human involvement at the time of execution (Yadav, 2015). Adegboye et al. (2023) shows that algorithmic trading plays an important role in improving price efficiency and reducing transaction costs, although in practice it can lead to extreme market volatility when multiple algorithms react simultaneously to market signals (Arnoldi, 2016; Bao et al., 2022; Yadav, 2015).

Along with the development of algorithmic trading, financial *engineering* is also becoming an increasingly important field. Financial engineering combines financial theory, applied mathematics, and statistics to design derivative instruments and complex risk management strategies (Jena et al., 2023). Strategies such as delta-hedging, risk-free arbitrage, and option pricing using the Black-Scholes model illustrate the integration between financial theory and advanced mathematical approaches, which often use logarithmic functions, cumulative normal distributions, as well as stochastic models (Nuugulu et al., 2023; Svirschi, 2012).

In the context of market volatility, a commonly used measurement is logarithmic return because it is additive to time and symmetrical to price changes (Miskolczi, 2017). Models such as ARCH and GARCH, developed by Engle (1982) and Bollerslev (1986), are widely used to model logarithmic return-based volatility. This model accommodates the heteroscedastic nature of volatility, i.e. fluctuations in variance that change over time (Dwarika et al., 2021; Kashyap, 2023). Furthermore, the GARCH (1,1)-M model allows conditional variance to be incorporated into the mean equation, thus analyzing the relationship between risk and return directly (Dwarika et al., 2021). In Indonesia, the GARCH model has been effectively used to analyze and predict daily stock returns, particularly in capturing time-varying and heteroskedastic volatility (Rio Rita et al., 2018). The GARCH model is also used in explaining the crypto market in the Indonesian and US stock markets (Dwi Darma & Utami, 2025).

H1: Algorithmic trading has a significant influence on stock market volatility.

Financial engineering is a financial science concept that combines financial theory, applied mathematics, and statistics to design and implement financial instruments and risk management strategies to create efficiency and innovation in the financial market (Neftci, 2008). One of the major milestones in financial engineering was the development of the Black-Scholes model, which revolutionized the way options valuation was conducted (Becker et al., 2024). This model uses a stochastic approach and efficient market assumptions to theoretically assess the price of options. In practice, this model is the basis for delta-hedging strategies, which are risk management methods used to keep the value of the portfolio neutral against changes in the price of the underlying asset. Strategies like this are widely applied by financial institutions in managing their derivatives portfolios (Morales-Bañuelos et al., 2022).

Furthermore, financial engineering is also closely related to the development of algorithmic trading, where quantitative model-based strategies such as statistical arbitrage, momentum strategies, and high-frequency delta hedging are automated through computer-based trading systems. In this context, financial engineering provides a theoretical framework and mathematical model, while algorithmic trading acts as a medium for the implementation of technology (Kim, 2007). Several previous studies have highlighted the strategic role of the interaction between algorithmic trading and financial engineering in influencing market volatility. Gasparin & Schinckus (2022) found that high-frequency trading contributes to flash crash events, which are sharp price declines in a very short period of time that are often associated with extreme log-return variances. In addition, delta-hedging techniques in options derivatives can magnify buying or selling pressure when small changes to the underlying asset demand significant adjustments in the portfolio

(Borovkova & Schmeck, 2017; L. Fan, 2021). When algorithmic strategies and financial engineering are used together, the potential for systemic volatility becomes higher, especially in highly liquid and digitized markets (Lin, 2017; Wehrli & Sornette, 2022a). Therefore, it is important to evaluate empirically how the combination of these two approaches affects market volatility, both as individual factors and in terms of interactions.

Previous studies such as those conducted by Andersen & Bollerslev (1998) and Glosten et al. (1993) have made extensive use of high-frequency data to model the dynamics of volatility and the influence of market information shocks. In the latest study, the use of the Generalized Method of Moments (GMM) is also becoming more widespread because it is able to handle the problems of endogeny and heteroscedasticity in dynamic panel regression (Dezsi et al., 2021; Diaz-Rainey et al., 2015). Utilizing a quantitative approach based on the GARCH (1,1)-M model and dynamic regression panels, this study seeks to fill gaps in the literature related to the simultaneous effects of algorithmic trading and financial engineering on stock volatility in emerging markets, particularly the Indonesian LQ45 Index. The main contribution of this study is to empirically test the integration of two cutting-edge financial approaches within modern statistical frameworks, which are still rarely studied simultaneously in the context of emerging markets.

H2: Financial engineering has a significant influence on stock market volatility.

Theoretically, while both individually can improve market efficiency in the short term, the simultaneous integration of trading algorithms with derivative instruments such as options or hedging strategies can instead create additional pressure on price stability. This is due to the potential for the creation of a feedback loop, where algorithms respond to price signals that have been distorted by derivative activity, thereby triggering higher endogenous volatility (Petchey, 2003). Berdasarkan teori di atas, berikut adalah mekanisme interaktif antara Algoritma Trading, Financial Engineering, dan Volatilitas Pasar, disertai feedback loop yang memperkuat siklusnya.

A[Algoritma Trading] → B[Percepatan Eksekusi Transaksi]
B → C[Lonjakan Volume Perdagangan]
C → D[Volatilitas Pasar ↑]

A → E[Pola Perdagangan Otomatis (HFT, Latency Arbitrage)]
E → F[Ketidakstabilan Harga dalam Jangka Pendek]
F → D

G[Financial Engineering] → H[Instrumen Derivatif Kompleks]
H → I[Leverage Tinggi & Eksposur Risiko]
I → D

G → J[Strategi Arbitrase & Synthetics]
J → K[Kesenjangan Harga dan Reaksi Pasar]
K → D

D → L[Market Feedback Loop]
L → A
L → G

In the dynamics of modern financial markets, algorithmic trading (A) plays a central role in accelerating transaction processes. The implementation of trading algorithms enables faster execution of transactions (B), where orders are completed within milliseconds, enhancing the responsiveness of market participants to new information (Hendershott et al., 2011). This technological advancement contributes to a surge in trading volume (C) as high-frequency systems process large numbers of orders in a short period. However, the escalation in volume may lead to increased market volatility (D), especially when driven by short-term signals rather than underlying fundamentals (Kirilenko et al., 2017). Beyond speed, algorithmic trading facilitates automated trading patterns (E), including High-Frequency Trading (HFT) and latency arbitrage, which capitalize on minute pricing inefficiencies and time lags across trading venues (Biais et al., 2015). These strategies often induce short-term price instability (F), as rapid order placements and cancellations distort the price discovery process. This contributes further to the amplification of market volatility (D), particularly during periods of market stress. In parallel, financial engineering (G) exerts a significant influence through the development of complex derivative instruments (H) such as credit default swaps, synthetic options, and structured products. These instruments frequently involve high leverage and elevated risk exposure (I), magnifying the effects of market movements and increasing systemic vulnerability. As a result, they become a critical driver of market volatility (D) during turbulent conditions.

Moreover, financial engineering includes arbitrage strategies and synthetic constructions (J) that exploit pricing inefficiencies across instruments or markets. Such strategies can trigger pricing gaps and abrupt market reactions (K) when large-scale positions are executed, intensifying short-term dislocations and contributing to higher volatility (D) (Marlowe, 2009). Ultimately, the convergence of these elements generates a market feedback loop (L), where increased volatility prompts further recalibration of algorithmic models (A) and structured financial products (G). This recursive mechanism reinforces the interdependence between technology-driven strategies and market uncertainty, making financial markets increasingly complex, fragile, and sensitive to minor shocks (Malynovska et al., 2025). Therefore, this hypothesis proposes that the combined effects of the two practices are not only additive, but complementary in magnifying price fluctuations.

H3: When algorithmic trading is carried out in a market that is also dominated by derivative instruments (financial engineering), market volatility tends to increase higher than when each is done separately.

METHODS

This study uses an explanatory quantitative approach, which aims to examine the causal relationship between the intensity of algorithmic trading and the use of financial engineering strategies on stock market volatility. This research is empirical and causal, where data is observed with daily or intraday frequency in the Indonesian stock market index LQ45 in 2024. The trading algorithm data in this study was obtained from various indicators such as order-to-trade ratio, transaction volume carried out by high-frequency trading (HFT), and message traffic recorded in certain units of time (Diaz-Rainey et al., 2015). Meanwhile, data representing financial engineering aspects are taken from derivatives contract positions such as options and futures, the volume of derivatives contracts traded, as well as delta-gamma hedging estimates on the relevant portfolios (Calhoun et al., 2014; Ji & Wei, 2023). To measure stock volatility, daily and intraday stock price data from selected companies that are members of the LQ45 index on the Indonesia Stock Exchange (IDX) are used. The data used is sourced from IDX, Bloomberg, and the BNI trading application.

Table 1. Research Variables

Variables	Definition	Key Indicators	References
Market Volatility (Y)	Size of stock price fluctuations	Return logaritmik: rt = $\ln(P_t/P_{t-1})$ dan model GARCH	(Dezsi et al., 2021; Perera, 2016)
Algorithmic Trading (X1)	Intensity of use of automated trading systems	Order-to-trade ratio, volume intraday	(Dubey, 2022; Dubey et al., 2022; Müller, 2021)
Financial Engineering (X2)	Derivatives strategy and portfolio engineering	Options & Delta Hedging Contracts	(Calhoun et al., 2014)

Variables	Definition	Key Indicators	References
Variable Control (Z)	Other factors that affect volatility	Stock liquidity, company size	(Ryu et al., 2024)

Source: the data is processed by the researcher, 2025

To capture the dynamics of conditional volatility and the simultaneous influence of two independent variables, the GARCH model (1, 1) and dynamic panel regression were used.
Stage 1: Estimated Return and Volatility.
Stock return (r_m) is calculated using the following log-return:

$$r_m = \ln(\frac{P_t}{P_{t-1}}) \quad (1)$$

According to (Dwarika et al., 2021) premium return is more appropriate to use because it considers excess return so that the calculation continues with the equation (2):

$$r_t = r_m - r_f \quad (2)$$

where, r_t: risk premium, r_m: market return and r_f: risk-free rate. We use annual Indonesian Government Bond (SUN) coupons which if daily will be calculated using the equation (3):

$$Daily\_rf = \left(1 + yearly_{rf}\right)^{\left(\frac{1}{365}\right)} \quad (3)$$

Stage 2: Estimation of daily volatility with the GARCH (1, 1)-M.
Since the GARCH (1, 1)-M model incorporates the standard deviation into the mean equation, the return affected by daily volatility is calculated using equation (4):

$$r_t = \mu + \sum_{j=1}^{p} \lambda j \sigma_{t-j}^2 + \varepsilon t, \qquad \varepsilon_t | F_{t-1} \sim N(0, 1) \quad (4)$$

where r_t: return at the t-time; μ: average return (mean); λ: Risk premium; σ_t^2: conditional variance; ε_t: error term, $\varepsilon_t | F_{t-1} \sim N(0, 1)$ with information conditions up to time t-1, error ε_t normal distribution.
After that, calculate the conditional variance using the GARCH model (1, 1):

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{p} \beta_j \alpha_{t-j}^2 \quad (5)$$

Where, σ_t^2: conditional variance at time t, i.e. the risk of return at time t that the model estimates; α_0: long term average variance; α_i: influence of past shock (ARCH term) σ_{t-i}^2: Surprise square error in the previous period (lag i); β_j: influence of past variance (GARCH term); α_{t-j}^2: conditional variance in the past (lag j).
Stage 3: panel regression with the Generalized Method of Moments (GMM) approach.
GMM is a very flexible and powerful moment-based estimation technique, especially in empirical economic analysis involving instruments and data conditions that are not ideal for classical methods. We use STATA 17 in implementing GMM.
Regression model used:

$$\sigma i_t = \gamma_0 + \gamma_1 X1_{it} + \gamma_2 X2_{it} + \gamma_3 (X1_{it}.X2_{it}) + \sum_{k=1}^{K} \delta Z_{it} + \varepsilon_{it} \quad (6)$$

where, σ_{it}: conditional volatility estimate of the stock i at time t, $X1$: the intensity of algorithmic trading, $X2$: Derivative exposure of financial engineering, $X1_{it} . X2_{it}$: interaction between two financial technologies, Z_{it}: variable control, ε_{it}: error term.

RESULTS AND DISCUSSION

A quantitative method was applied, employing the GARCH(1,1)-M model to estimate volatility and dynamic panel regression using the Generalized Method of Moments (GMM) to address potential endogeneity and heteroskedasticity. The analysis focused on 40 LQ45 index stocks with daily data throughout 2024, using the order-to-trade ratio as a proxy for algorithmic trading and derivative contract volume to represent financial engineering. Before model estimation, a descriptive analysis was conducted to capture key patterns in volatility, trading activity, and derivative dynamics in the Indonesian stock market. The subsequent sections present the core empirical findings, followed by a detailed discussion of their implications for financial market theory and policy in the digital era.

Statistics descriptive

Based on the analysis of daily logarithmic return data during the period January to December 2024, this study concludes that algorithmic trading and financial engineering activities have a real relationship with stock market volatility patterns. Table 2 shows descriptive statistics as below:

Table 2. Statistics descriptive

	Mean	SD	Min.	Median	Max.
Return Logaritmik (r_t) (%)	0.041	0.59	-3.12	0.03	2.84
Varians Return (Var(r_t))	0.00034	0.00017	0.00010	0.00031	0.00110
Order-to-Trade Ratio	1.27	0.38	0.62	1.21	2.45
Volume Derivatif (Rp Miliar)	85.00	37.50	25.30	80.10	161.20

Source: the data is processed by the researcher, 2025

The average daily logarithmic return was recorded at 0.041% with a standard deviation of 0.59%, which indicates that although the market is generally moving positively, there are quite dynamic fluctuations from day to day. This is reinforced by the return variance value of 0.00034, with the maximum return value reaching 2.84% and the minimum value of -3.12%, indicating an extreme price movement at a certain time, which has the potential to be triggered by the algorithm's simultaneous reaction to market signals.

Algorithmic trading activity measured through the order-to-trade ratio shows an average of 1.27, with a maximum of 2.45, reflecting a high volume of orders that are not always followed by the execution of actual transactions. This phenomenon leads to pseudo-liquidity that can accelerate volatility when multiple algorithms interact at the same time. Meanwhile, the volume of daily derivatives contracts – which is a proxy for the intensity of financial engineering – was at an average of IDR 85 billion per day, with a considerable deviation, namely IDR 37.5 billion, and a value range between IDR 25.3 billion to IDR 161.2 billion. This suggests that the use of derivative instruments such as options and futures is not only widespread, but also volatile, reflecting adaptive reactions to market dynamics.

Regression Results

Table 3 presents the GARCH(1,1)-M regression results, which capture conditional volatility while directly incorporating the effects of algorithmic trading and financial engineering into the mean and variance equations.

Table 3. Dynamic Panel Regression Results

	Coefficient (γ)	Std. Error	t-Statistics	p-Value
Konstant (γ_0)	0.0054	0.0018	3.00	0.003*
X_1: Algorithmic Trading	0.2101	0.0765	2.75	0.006*
X_2: Financial Engineering	0.3178	0.0892	3.56	0.0004*
$X_1 \cdot X_2$ (Interaction)	0.1213	0.0487	2.49	0.013**
Z: Company Size	-0.0045	0.0019	-2.37	0.018**
Z: Stock Liquidity	-0.0078	0.0032	-2.44	0.015**
R^2 (within)	0.412			
Overall F test (p-value)				0.000
Hausman Test (p-value)				0.027

Notes: Variable dependent: σ_{it}; (*) confidence level at 1%, and (**) at 5% confidence level.

Source: the data is processed by the researcher, 2025

The results of the analysis show that the H1 Hypothesis is accepted, where algorithmic trading (X_1) is proven to have a positive and significant effect on stock market volatility ($\gamma_1 = 0.2101$; $p = 0.006$). These findings indicate that the higher the intensity of the use of algorithms in stock trading – which in this study is driven by an order-to-trade ratio – the greater the price volatility caused. This findings are in line with empirical evidence showing that algorithm-based trading strategies, while improving short-term liquidity efficiency, also tend to amplify price fluctuations in sensitive market conditions (Yadav, 2015). These results are also consistent with agent-model-based studies that show that high-frequency traders who respond to price signals simultaneously can generate endogenous volatility and even contribute to phenomena such as flash crashes (Leal et al., 2016). This is consistent with Khan et al. (2024) that algorithm-based trading activities, while improving short-term liquidity efficiency, also have the potential to create wilder price dynamics on sensitive market conditions. Theoretically, this effect can be explained through algorithmic reactions to price signals that result in endogenous volatility in the market structure (Zhang & Zhang, 2024).

Furthermore, the H2 hypothesis is also accepted, showing that financial engineering (X_2) has a positive and significant effect on market volatility ($\gamma_2 = 0.3178$; $p < 0.01$). The use of financial engineering techniques such as derivative contracts and delta hedging strategies – which in this study is measured through options volume – increases stock price uncertainty. According to (Carr & Wu, 2017) financial derivatives, while useful as hedging instruments, can also amplify the volatility feedback effect when used aggressively by market participants. In this context, small changes in the value of the underlying asset can trigger the need for massive position adjustments, which then impact more extreme price fluctuations. Christensen & Hansen (2002) showed that high options market activity is closely correlated with increased volatility in both implied and realized. Volatility-related instruments such as variance swaps and volatility futures can be a transmission channel for shocks, thereby prolonging the duration and intensity of volatility in the stock market (Naeem et al., 2024). In addition, Pruna et al. (2020) explain that demand for derivatives instruments under conditions of risk aversion and information asymmetry can drive excessive volatility, exceeding the fundamental value of the asset.

Interestingly, the H3 Hypothesis is also statistically supported, where the interaction between algorithmic trading and financial engineering ($X_1 \cdot X_2$) has a positive and significant coefficient of volatility ($\gamma_3 = 0.1213$; $p = 0.013$). This suggests the presence of complementary effects, not just additives, when both practices are applied simultaneously. It means the use of algorithms in a market dominated by derivative instruments generates additional pressure on price stability. This finding confirms (Anas et al., 2024) that when quantitative and derivative strategies are integrated in the modern trading ecosystem, they can create an amplification mechanism against market shocks, especially through feedback trading loops and high-frequency risk transmission. Leal et al. (2016) describes when HFT responds to price signals that have been formed by derivative activity, thus forming a feedback loop that exacerbates price dynamics. In the article titled "Overreacting Algorithms in Financial Markets", Gerner-Beuerle & Zierahn (2023) a feedback loop creates a condition of amplification of volatility that is endogenous, that is, volatility that arises not due to changes in fundamental information, but rather due to the simultaneous interaction of two systems that reinforce each other: algorithms and derivatives. Although it does not specifically discuss derivatives, Wehrli & Sornette, (2022) provides theoretical evidence that excessive volatility in the market is often the result of endogenous amplification through feedback mechanisms. This principle is relevant in explaining why the combination of trading algorithms and derivatives reinforces the volatility of the market structure.

As for the control variables, company size and stock liquidity show a negative and significant influence on volatility. This means that stocks from large companies as well as stocks with high liquidity levels tend to have lower volatility. Large companies with high market capitalization and good transaction liquidity have more stable risk exposure due to their wide coverage of public information and a more diversified investor base (Anas et al., 2024). Overall, these results confirm that the current volatility dynamics of the stock market cannot be separated from the simultaneous role between advances in trading technology and financial innovation. The integration of the two reinforces the need for adaptive risk management systems as well as regulatory policies that capture the complexity of modern market microstructural interactions.

Although this research makes an important contribution to understanding the influence of algorithmic trading and financial engineering on stock market volatility, there are some limitations that need to be noted: *first*, the limited proxy of variables. Order-to-trade ratios, and financial engineering are proxied by the volume of derivative contracts that do not fully describe the complexity of the strategies used by market participants, such as latency arbitrage algorithms or non-standard derivative structures (exotic options), so results can be partial. *Second*, a quantitative approach without analysis of market behavior. This study is completely quantitative and does not examine the adaptive behavior or strategies of investors and financial institutions. In fact, risk perception and investor sentiment can interact with technology and financial engineering in creating volatility.

CONCLUSION

This study concludes that both algorithmic trading (X_1) and financial engineering (X_2) have a positive and significant influence on stock market volatility. In addition, the interaction between the two also amplifies the effects of price volatility, indicating that the simultaneous use of algorithmic technologies and derivative instruments creates additional pressure on market stability. By applying dynamic panel regression models and conditional volatility estimation using GARCH (1, 1)-M, this study not only confirms previous empirical findings, but also demonstrates an original contribution in the form of quantitative evidence of the effects of complementary interactions between trading technologies and financial engineering. This study has two main limitations. First, the proxy variables – order-to-trade ratio and derivative contract volume – do not fully capture the complexity of market strategies such as latency arbitrage algorithms or non-standard derivatives. Second, the purely quantitative approach does not account for the adaptive behavior of investors and financial institutions.

Implication, regulators and market participants need to improve microstructural risk monitoring systems and pay attention to the combined impact of technology and derivatives on financial stability. This research opens up space for further exploration of behavioral dimensions, algorithmic regulation, and systemic influences, especially in the context of highly globalized and digitized markets.

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