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ARTICLE

Microstructural Impact of Algorithmic Trading on African Equity Markets: A Causal Evaluation of Efficiency, Liquidity, and Stability

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Abstract

The study provides a detailed empirical evaluation of the effect of the automated trading otherwise known as algorithmic trading (AT) on market efficiency, liquidity, and steadiness in ten main African equity markets. The study offers an in-depth empirical assessment of the impact of AT on market efficiency, liquidity, and stability in ten major African equity markets. To effectively close a critical gap in the literature on research on frontier-markets, the study applies an integrative approach to methodology, which combines along with intraday market microstructure evidence, causal inference approaches and machine learning practices. The intensity of algorithmic trading was measured using microstructure tools, and the study measures the consequential variables of the which includes return autocorrelation, bid ask spread, market depth and volatility persistence. We adopt quasi-experimental designs that exploit market-structure reforms for causal identification on a methodological level. By using a Finite Mixture Model, the analysis first classifies continent exchanges into Class 1 Deep Markets (42% probability, average capitalization \$245.6B) and Class 2 Thin Markets (58% probability, average capitalization \$18.7B). It shows that AT intensity is highly concentrated in deep capitalized venues. Using a robust double machine learning framework with 5-fold cross-fitting, we estimate the causal effects of quoting automatically. The estimates indicate that an increase in Message-to-Trade Ratio (MTR) and Cancellation-to-Trade Ratio (CTR) compresses the transaction cost significantly. In particular, the effective spread decreases by 0.156 ($p < 0.01$) and 0.167 ($p < 0.01$), respectively, while increasing log market depth by 0.098 and 0.087. AT robustly improves informational efficiency, reducing Kyle's λ by up to 0.021 units. We quantify a distinct structural trade-off: higher AT activity also leads to a statistically significant rise in realized volatility (MTR effect: +0.027; CTR effect: +0.031). Predictive modeling based on Long Short-Term Memory (LSTM) neural networks demonstrates that high AT environments considerably enhance predictability, despite an increase in baseline volatility; improving out-of-sample RMSE forecasting performance by 11.9% and boosting R2 by 18.5%. To sum up, our high-frequency anomaly detection reveals that AT does not change the market shock frequency baseline of 1.92%. However, it provides a significant shock absorber that compresses the anomaly duration by 3.6 minutes, helps the market recover post-shock in 16.6 fewer minutes, and reduces the extreme volatility multipliers from 4.2x to 3.8x. Most prominently, findings indicate that the African Trade (AT) Exchange is essential for market liquidity and resilience, although the share is not equal. The study finds that a common feature of algorithm trading is its capacity to improve informational efficiency, contributing positively to the information quality of prices. It does so by reducing the return autocorrelation and order flow predictability. Having state-dependent dynamics implies that the sensitivity to shocks runs through the rich posterior distribution of shocks for various parameters. To the point, the effects are quite heterogeneous since they are distinctly moderated by the original depth of the market and the structure of the exchange. A customized policy prescription study for African regulators and market actors to illustrate the need to measure visibility, establish robust market structures, and execute conditional reforms in line with the specifics of the market situation and liquidity needed.

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1. INTRODUCTION

The concept of market efficiency has been studied for its low-frequency predictability of returns in Africa, and the standard hypothesis test regimes which are influenced by Fama [1]. On the other hand, the impact of automated trading otherwise known as algorithmic trading (AT) is evident on a microstructure, such as quote revision, cancellation intensity, inventory control and price impact, which are difficult to measure empirically with the current methods. This lack of fit between the variables that are explored in traditional studies and the substantive processes that are caused by the modernization of the market create three fundamental methodological issues. The first issue is that of limitations in measurement. However, most studies on Africa do not report AT intensity directly because of the data availability. The AT footprint, however, can frequently be found in proxy variables, such as the message-to-trade ratio, the quote-to-trade ratio, the cancellation ratio, the trade size, the intraday order book [2,3]. Without these specific adjustments, it is difficult to determine if the spreads, volatility, or predictability of returns exhibited are real and a function of automation or simply a function of some anecdotal shifts in the investor population and/or macroeconomic risk.

The other issue is constraints of identification. Even if there are signs of improvement in the market, such as rising in quality, this does not necessarily imply that it is attributed to AT. Adoption of AT is usually associated with other modern changes- including platform upgrades, changes in fee structure and changes in overall regulatory changes [4]. Thus, the strong inference needs quasi-experimental designs, which generate reasonable counterfactual paths and the ability to isolate discontinuities or exogenous shocks, which can be attributed to the deployment of AT. The third problem is related to dynamic constraints. Market efficiency and stability are dynamic in nature. In the presence of shocks, if they are not dissipated, that is, if the returns and the volatility have long memory, there is no complete diffusion of information, meaning that there are still frictions [5]. Failure to express this persistence in a fractional integration way could lead to wrong estimation of the volatility and predictability processes. Furthermore, the impact of AT will vary depending on the market regimes: an expansion during normal times will be followed by increased instability when stressed, and aspects of asymmetry and regime switching need to be explicitly modeled [6,7].

The driving force behind the research is five questions which underpin the understanding of the impact of automated trading on African stock markets. First, it aims to establish if these markets are any more efficient because of algorithmic trading. Secondly, it investigates if algorithmic trading decreases return autocorrelation and enhances price discovery. Third, the influence of automated trading on bid-ask markups and market liquidity is explored. Fourth, it examines whether algorithmic trading leads to higher or lower intraday volatility and tail risk. To sum up, it examines if there are differences between the impact of algorithmic trading on exchanges, sectors and regime.

The main goal of this study is to empirically evaluate the efficiency, liquidity and stability effects of algorithmic trading on African stock markets using causal, non-linear and high-dimensional econometric and machine-learning methods. In particular, the study seeks to quantify the level and dynamics of automated trading on selected exchanges on the African continent. It also aims to assess weak form and microstructure efficiency both prior to and following major algorithmic and regulatory changes. Moreover, the study attempts to explore the long memory character of returns and volatility with rising algorithmic activity. It will explain how algorithmic trading affects liquidity, spreads and volatility. Another goal of the study is to model latent market structures and cross market heterogeneity in the effects of algorithmic trading. The research will be evaluated if structural changes are detectable in machine learning forecasts and anomaly detection.

The study is essential in the following ways: To regulators, it provides empirical proof that can inform the reforms, which include cancellation policies, design of tick-size, structure of auction, and interruption of volatility. For exchanges, it explains what attributes of exchanges have resulted in enhanced liquidity provision and price discovery, and which ones have contributed to fragility. To market participants, it enhances the knowledge of quality execution and risk in the markets which shift towards an increased automation. The contribution is particularly relevant in situations that involve serious policy decisions in context of the market-design modernization in thin-liquidity conditions [8]. The research will be organized in six sections. Section 2: a thorough analysis of the available empirical studies that are published in 2023-2026 and summarize the findings and methods is performed. The methodology is detailed in Section 3, as are the model specifications and description of the specific variables and data construction steps. The results are presented in Section 4. Results and the test of the hypotheses are discussed in section 5 and the course of further research and the policy recommendations are summarized in section 6, the conclusion of the work.

2. EMPIRICAL REVIEW

Typically, the degree of liquidity is measured by the quoted spread, the effective spread and depth [9]. Recent research enables the accuracy of the measurement and its comparability across assets to be enhanced by developing high-quality spread estimators and by separating out elements of the transaction costs and adverse selection [10]. They discovered that strong spread estimators based on open, high, low, and close (OHLC) data are useful for liquidity studies [10]. This methodological result is of special value in markets where trading is scarce, like in emerging markets. Nimalendran, Rzayev, and Sagade noted the sniping risk can cause equity HFT to expand options spreads [11]. This study, across U.S. markets, suggests that spillover costs can emerge from algorithmic trading operations. The use of algorithms to trade enhances spreads [12]. Rzayev et al. found that the liquidity benefit of passive HFT can be mitigated by the aggressive HFT [13]. This discovery, in the context of developed markets, indicates that the impact of algorithmic trading relies on the types of trading strategies involved.

Nimalendran, Rzayev, & Sagade show an increase in options market spreads over aggressive HFT in equities, which is evidence of such an adverse selection and sniping-risk channel that is exacerbated in the circumstances with parity violations [11]. This is in line with the hypothesis that, even when it enhances liquidity in normal times, AT can enhance short-term instability. Other presentations point towards the need to quantify volatility on the basis of realized volatility and jump or tail measures and not only on the basis of daily conditional variance as AT effects can be intraday [14]. In the presence of a long memory of the shocks [15], so that the shocks cannot be absorbed quickly, market quality becomes a persistent feature: there is no complete clearing and slow information absorption as volatility and returns are long-memory [15]. In the context of the African setting, the current evidence continues to suggest both of these phenomena inefficiency persistence and weak-form inefficiency deviation [16] raising the question of whether an increase in the intensity of algorithms is correlated with the decrease in persistence. This is the motivation to incorporate the concept of fractional integration in a causal context, as opposed to considering it just another descriptive endeavour.

Also, the exogenous shock identification to AT participation or infrastructure changes provides a better indication that AT can speed up information incorporation in comparison to basic tests of return autocorrelation [17]. However, the conflicting results persist, particularly with regard to the volatility and stability effects. This suggests channels of fragility [11], as there is some indication that adverse selection and sniping risk may explain higher costs of liquidity in correlated markets. Furthermore, the liquidity provision in the types of traders can be market-specific meaning that the AT may be more or less liquid in a given market. The lack of causal evidence on the relationship between AT adoption or reforms and market efficiency and liquidity outcomes, and the lack of high-frequency microstructure research in a wide range of African exchanges are all considered to be substantive gaps in the African context. Methodological gaps involve the studies of African market quality that did not utilize advanced econometric techniques like fractional integration, SCM, RDD and DML; and the lack of integration of ML-based anomaly detection with econometric inference and policy interpretation [18]. This is a research paper that focuses on the following gaps: intraday microstructure measurement, long-memory diagnostics, quasi-experimental design, latent heterogeneity panels and causal ML inference are integrated within a single African-based framework. This design will ensure that the outcome will be able to answer the regulators and exchange designers not only to the questions of statistical predictability.

In the literature, the impact of algorithmic trading on market efficiency, liquidity and volatility has been investigated, but no studies have done this in an Africa-specific context using the methodology of intraday microstructure data and modern causal inference techniques. The contribution is four times as large. First, it offers a combined measure of algorithmic trading rates across numerous African exchanges, including widely-used microstructure proxies such as the message-to-trade ratio and cancellation rates, as well as exchange-provided indicators, if available [19]. Second, it runs microstructure efficiency tests, using intraday return autocorrelation, variance ratio tests and price impact tests that are all able to capture the order-book channel and thus, no longer relies on daily returns scrutinies only [17].

Third, it makes use of a composite causal identification toolkit that consists of the DiD, Synthetic Control Methods (SCM) and Regression Discontinuity Designs (RDD) tools that help make credible inferences about discrete market-structure reforms, such as ticksize manipulations, auction restructurings and platform upgrades [20]. Fourth, it incorporates dynamic heterogeneous modeling, such as long-memory or fractional integration for measuring changes in persistence, latent heterogeneity panel for the classification of distinct market types and Double Machine Learning (DML) for estimating causal effects under high-dimensional confounding [21]. This is in line with the current state of the art in the wider literature: researchers are increasingly more and more integrative in their use of sound identification procedures and rigorous inference methods to eliminate spurious findings of algorithmic trading and market quality [19].

3. METHODOLOGY

Research Design and Approach

The study uses an integrative methodological approach and empirically assesses the performance of algorithmic trading (AT) on the market efficiency, liquidity, and stability of 10 main equity markets in Africa. The research design combines intraday market microstructure analysis, machine learning methods, and causal inference methods to address the multifaceted and high-frequency aspects of contemporary trading. The study uses quasi-experimental designs with market-structure reforms as anchors to help identify the causal impact of AT relative to the larger macroeconomic context. The methodological structure of this study begins with descriptive and stylized facts, in which the time paths of the strength of algorithmic trading are described, differences in the bid-ask quotations and the market depth across exchanges are compared and the intraday seasonal dynamics are described

This phase also analyses the interaction between algorithmic trading and periods of stress in the market. This foundational analysis is crucial as it sets the parameters for further testing; helping to determine the allowable window of treatment, select appropriate counterfactuals for the Synthetic Control Method (SCM), and guide the robustness testing that follows. The tests deployed in the link between the intensity of algorithmic trading and the market quality indicators (such as depth and spreads) were next the unit root test and co-integration test. It is not a prerequisite here to prove causality, but only to show the existence of a coherent and long-run co-movement as compatible as structural modernization of markets resulting from algorithmic trading.

The measures of analysis comprise the microstructural and machine learning analysis at the level of stock level intraday aggregate and exchange level aggregates and indexes, and the panel causation and heterogeneity classification level. The study also employs fractional integration and long-memory models: the ARFIMA models of the returns and the FIGARCH models of the volatility, using the framework of fractional integration that are proposed by Baillie et al., 1996 and by Hosking, 1981 [5,22]. The null hypothesis tested here is that when augmented algorithmic trading behavior is present the persistence of market moves is reduced, that is the fractional differencing exponent, d, should be smaller. This would help confirm the theory behind algorithmic trading that it results in an efficient spread of information throughout the market. The study employs a DiD technique that measures the causal effect of automated trading by comparing the data for the treated and control groups before and after the reform. The Synthetic Control Method (SCM) was also used to construct counterfactual exchange-level outcomes, where the reforms are localised. The synthetic control unit was developed by assigning weights to a set of untreated exchanges and then measuring an outcome like efficiency, liquidity, volatility.

The study in the RDD exploits the deterministic nature of cut-off points, such as the size of the tick or the price level. In this design, local identification is used, with interest in assets that are as close as possible to investigate the effect of algorithmic trading on the competition of quoting and the supply of liquidity. As for the algorithmic trading, the study uses panel models of heterogeneity, such as latent factor-augmented panel model or finite mixture models, to account for the heterogeneity in the effects of algorithmic trading. These models can identify hidden market regimes, e.g., thin markets vs. deep markets and interpret the difference between the effects of algorithmic trading on the two types of markets. Depending on the market conditions, this analysis can offer insights which can be applied for policy customization.

The study also utilizes DML techniques to estimate the causal effects of algorithmic trading proxies on market outcomes. This method uses flexible controls and nuisance estimation that is nonlinear, thereby minimizing the high dimensional confounding bias [21]. DML can be particularly convenient when one or more of the confounders is complex, such as market-state variables, order-flow properties, and macroeconomic controls [23,24]. Volatility and returns prediction, as well as anomaly detection such as flash crashes and liquidity droughts, were achieved using the LSTM networks [18]. The LSTM technique can potentially detect structural shifts in the market, especially in high-algorithmic-trading environments after the reform. If these are the regimes where anomalies are clustered, it is indicative of the idea that algorithmic trading causes instability. The decreasing anomalies, on the other hand, would indicate a market-stabilizing impact of algorithmic trading.

First-order and higher-order autocorrelations were computed at a uniform interval (e.g., 1-, 5-, and 15-minute returns) both intraday and daily. The variance ratio tests were applied to identify the deviations from a random walk, and the multi-horizon variance ratios were applied to test the market efficiency followed by Lo and MacKinlay [25]. Price impact measures were calculated by applying regression-based models: a Kyle-style lambda proxy based on returns and signed volume was used to better reflect the market's reaction to trades. Liquidity was also calculated from quoted and effective spreads, where applicable, with spread decomposition techniques being employed to separate adverse selection elements of the spreads, following the approach proposed by Glosten and Milgrom [26]. Realized volatility was explored by intraday returns and conditional volatility models such as EGARCH and TGARCH were used. Tail risk measures are calculated using extremes or jump proxies as in Barndorff-Nielsen and Shephard and Nelson [27,28]. Further, the measurement of order book depth was done using the best level of the order book and, if applicable, multi-level cumulative depth.

Algorithmic trading is proxyable using a variety of key explanatory variables which capture different aspects of the algorithmic activity. Message-to-trade ratio (MTR) was computed as the average for all the orders, changes, and cancellations divided by the number of trades that were actually executed. The number of cancellations was divided by the number of trades and/or units of time, resulting in a cancellation rate (CTR). The quote-to-trade ratio (QTR) is a measure of the number of quotes issued for each trade made, which is indicative of the level of quote activity related to algorithmic trading. Further understanding of the algorithmic trading market behavior is provided by trade-size distribution measures, including the percentage of small trades and shifts in median or quantiles, and fragmentation signatures. If any flags are available showing that the direct algorithmic trading is being conducted, these are also taken into account.

Control variables are incorporated in the analysis to allow for the consideration of other factors that may affect the efficiency and liquidity of the market. Firm or market controls refer to variables such as market capitalization, turnover, free float and any other base variables that reflect the general liquidity of a market, such as the Amihud illiquidity ratio [29]. To capture the overall market conditions that can affect the dependent variables, market state variables like lagged volatility, volume shocks, and state variables of liquidity are included. The effects of macroeconomic and global risk factors are also included, such as domestic policy announcements, commodity price shocks for commodity-sensitive markets, and VIX (an overall measure of market risk).

Table 1. Hypotheses-to-Tests Mapping

Hypothesis	Core Test Statistic	Primary Model(s)	Confirmation Pattern
H_1	ρ_1, VR(q)	DiD/SCM/RDD; DML	Post-reform ↓ autocorrelation; VR → 1
H_2	Spreads, Depth	DiD/SCM; Microstructure regressions; RDD	Spreads ↓, Depth ↑
H_3	Fractional d	ARFIMA/FIGARCH with AT interaction	d ↓ as AT rises
H_4	RV, EGARCH persistence	EGARCH/TGARCH + event windows + ML anomalies	Short-run RV ↑; Long-run persistence ↓
H_5	Regime effects	Mixture/Factor panels; Interactions	Sign/Magnitude differs by market type

Empirical Models and Estimation Strategy

To rigorously test the hypotheses, the study deploys a multi-tiered econometric and machine learning framework.

Causal Inference: Quasi-Experimental Design: To address potential endogeneity between AT intensity and market quality, the study utilizes a Difference-in-Differences (DiD) framework, exploiting staggered market-structure reforms across the ten African exchanges (e.g., the introduction of co-location services or API upgrades). The baseline panel regression model is specified as:

$$Y_{i,t} = \alpha_i + \gamma_t + \beta_1(Post_{i,t} \times Treated_i) + \delta X_{i,t} + e_{i,t} \qquad (1)$$

The model is designed to evaluate the impact of algorithmic trading (AT) on market quality metrics such as the Effective Spread, ρ_1, and RV. In this model, $Y_{i,t}$ represents the market quality metric for asset i at time t. The term $Post_{i,t} \times Treated_i$ serves as the DiD estimator, capturing the effect of the introduction of AT-facilitating reforms on the asset's market quality. The vector $X_{i,t}$ includes time-varying control variables such as market capitalization and baseline trading volume, which account for factors that may influence market quality independently of the reform. To control for unobserved heterogeneity, α_i and γ_t represent asset and time fixed effects, respectively, ensuring that the analysis accounts for both asset-specific characteristics and temporal variations in market conditions. This model allows for an accurate assessment of how the introduction of algorithmic trading influences market quality, isolating the effects of the reform from other potential influences.

Machine Learning-Finite Mixture Models (FMM): For the reason that market microstructure relationships often exhibit regime-switching behaviors (e.g., normal trading periods versus high-stress volatility events), traditional linear models may be insufficient [30]. A Finite Mixture Model (FMM) is employed to cluster the data into latent market states without *a priori* threshold definitions. The probability density function for the market quality variables is modeled as a weighted sum of K component densities:

$$f(y|x,\Theta) = \sum_{k=1}^{K} \pi_k\,(x,\alpha).\,g_k(y|x,\theta_k) \quad (2)$$

In this framework, let K be the unobserved market regime, for instance K=2 for steady versus fragile states, reflecting the nature of the underlying market. The mixing probability for each regime, π_k, is allowed to be a function of AT intensity, measured for example in terms of the Message-to-Trade Ratio (MTR) and Cancellation-to-Trade Ratio (CTR). Using machine learning algorithms, the model is able to capture different activities of algorithmic trading by mixing the probabilities of underlying algorithms. The conditional density of the market quality metric within each regime is denoted as g_k; that is how the market quality occurs over the different market conditions. Using a DiD causal framework in combination with Finite Mixture Model (FMM), this technique not only isolates the average treatment effect of algorithmic trading on African equity markets but also reveals how algorithmic trading increases the likelihood of switching from stable to volatile regime and vice versa.

Fractional Integration and Long-Memory Models

While the DiD and FMM frameworks address causal average effects and regime-switching, they do not fully capture the time-series persistence of market dynamics. To evaluate the impact of Algorithmic Trading (AT) on the long-memory properties of the African equity markets, the methodology is extended to incorporate fractional integration models. Following the foundational frameworks of Hosking and Baillie et al. [5,22], this study models the persistence in both asset returns and market volatility. The central hypothesis tested here is that augmented AT behavior enhances market efficiency and accelerates price discovery, thereby reducing persistence in market movements. Consequently, an increase in AT intensity should be reflected by a statistically significant reduction in the fractional differencing exponent, d.

Modeling Return Persistence: The ARFIMA Framework

To test for long memory in the mean of the return series (a direct test of the Efficient Market Hypothesis under H_1), the study utilizes the ARFIMA (p, d, q), model [22]. The ARFIMA model for the return series r_t is specified as:

$$\Phi(L) = (1-L)^{d_m}(r_t - \mu) = \Theta(L)e_t \quad (3)$$

In this model, μ is the mean over time. The relationships between the current and past values of a station are expressed using the lag operator, L. The AR and MA polynomials, denoted $\Phi(L)$ and $\Theta(L)$, respectively architected of orders p and q, incorporate past returns and past error contacting short-run adjustment of returns series. Therefore, these past returns and errors are assumed able to exert themselves on the current price adjustment AD. To account for long-memory dependencies in the data, the fractional differencing operator $(1-L)^{d_m}$is applied to the mean equation, where d_m represents the fractional integration parameter for returns, allowing for fractional differencing in the time series. Also, e_t is the discrete-time white noise error term, which contains the series random fluctuations, not explained by the series model. The approach provides us a comprehensive framework for modeling return dynamics with short-run and long-run dependencies.

Hypothesis Testing (d_m): If $d_m \in (0,0.5)$, the return series exhibits long-memory (positive dependence and persistence). If $d_m = 0$, the series follows a short-memory random walk, indicative of high market efficiency. The study hypothesizes that as AT intensity (MTR, CTR) increases, d_m decreases toward zero.

Modeling Volatility Persistence: The FIGARCH Framework

To address the steadiness and volatility persistence of the market (H4), the study models the conditional variance using the FIGARCH (p, d, q), model presented by Baillie et al. and popularized by Tayefi & Ramanathan [5,31]. Financial volatility often exhibits hyperbolic decay in its autocorrelation function, which typical GARCH models cannot absorb [32,33]. The FIGARCH model characterizes the conditional variance σ_t^2 as:

(4)

$$\varphi(L)(1-L)^{d_m} e_t^2 = \omega + [1-\beta(L)](e_t^2 - \sigma_t^2 \quad (5A)$$

In this model, ωrepresents the constant, which sets the baseline level of volatility [34]. The lag polynomials $\varphi(L)$ and $\beta(L)$, with orders q and p respectively, capture the ARCH and GARCH effects, which reflect the relationship between past squared returns (ARCH) and past volatility (GARCH) in determining the current level of volatility. Differencing operator $(1-L)^{d_v}$is applied to the variance equation to account for long-memory volatility dependencies, where d_v is the fractional integration parameter for volatility. This allows the model to capture volatility persistence over time, enabling a more flexible and accurate representation of the underlying volatility dynamics.

***Hypothesis Testing (d_v)*:** The parameter d_v measures the persistence of volatility shocks [35]. A d_v closer to 1 implies that volatility shocks have a permanent effect on market steadiness, while $d_v \in (0,1$ indicates a slow, hyperbolic decay of shocks. The study evaluates whether the proliferation of AT structurally alters d_v. A reduction in d_v during high-AT regimes would suggest that algorithms help absorb shocks and restore market steadiness more rapidly, whereas an increase would indicate that AT exacerbates long-term volatility persistence.

Integration with the Causal Framework: To bridge the long-memory models with the causal inference design, the fractional differencing parameters (d_m and d_v) were estimated over rolling intraday windows. These time-varying exponent estimates were then utilized as dependent variables in the previously established Difference-in-Differences (DiD) and Finite Mixture Model (FMM) regressions. This allows the study to empirically isolate whether exogenous shifts in algorithmic trading structurally mitigate the long-memory properties of African equity markets.

Variable Measurement/Construction

The core variables, mapped to their underlying theoretical constructs, are categorized into AT intensity, market efficiency, liquidity, and volatility metrics.

Measuring AT Intensity: Due to the challenges in directly identifying AT in exchange feeds, the intensity of algorithmic trading is commonly proxied using established microstructure message traffic metrics [36,37,38]. There are many measures used to assess the activity of algorithmic trading, such as the Message-to-Trade Ratio (MTR) [39,40]. It is determined by the ratio of all order book messages (messages with orders, cancellations and modifications) to all trades. Higher MTR suggests higher involvement of algorithmic traders in the market because these traders tend to send a lot of messages for every trade they make [39,40]. In addition, the Cancellation-to-Trade Ratio (CTR) is employed to measure the ratio of cancelled orders to executed ones [41]. This measure reflects the high-speed order changes typical of algorithmic orders, which indicate the dynamic aspect of their trading behavior [41]. Combined these metrics give a proxy for AT intensity and can give some insight of the intensity of algorithmic activity in markets where direct identifiers do not exist.

Dependent Variables: Market Quality Constructs: The explained factors in this study are the constructs of market efficiency and quality, represented by the various return, liquidity and volatility measures. That is, the consequential effects of algorithmic trading (AT) are captured on the four main dimensions of the market. The first dimension is market efficiency, to be assessed in terms of two metrics. First-Order Return Autocorrelation (ρ_1) is the first metric that measures the predictability of short-term returns [42]. Based on the hypothesis that algorithmic trading makes the price discovery process faster, one would expect that ρ_1 would be lower, meaning the less predictability and more efficient market. The second measure is Variance Ratio (VR(q)) that evaluates the random walk nature of asset prices at horizon q, as in Babu [43]. If the market is more efficient, then the VR(q) will be very close to 1, which means there is no predictable pattern in asset prices [44]. These two indicators are important insights into the effectiveness of the marketplace in reacting to algorithmic buying and selling.

In the liquidity dimension, two types of spreads are analyzed: the Quoted Spread (QS) and the Effective Spread (ES). The QS measures the explicit cost of trading and is calculated as the difference between the best ask (At) and best bid (Bt), normalized by the midquote (M_t), that is $((A_t - B_t)/M_t)$ [45]. The Effective Spread captures the actual execution cost for market orders, where P_t is the trade execution price$(2[|P_t - M_t|/M_t])$ [46]. With increased AT activity, both spreads are expected to decrease, signaling an improvement in liquidity. Additionally, Depth@Best is measured by the total volume of shares available at the best bid and best ask [47]. Higher AT intensity is expected to result in greater market depth, which improves liquidity.

The third dimension, price discovery, is measured using Kyle's Lambda (λ), which estimates the price impact per unit of signed trading volume [48]. This metric serves as an inverse proxy for market depth and liquidity resilience, with a decrease in λsignifying improved liquidity. The steadiness of the market is examined through two metrics: Realized Volatility (RV) and Tail Risk (Jump/ES). Realized Volatility is measured as the sum of squared intraday returns and the theoretical impact of AT on RV is uncertain. Meanwhile, Tail Risk is assessed using high-frequency jump indicators and Expected Shortfall (ES), capturing short-run liquidity droughts or flash-crash vulnerabilities [49], which are hypothesized to increase with the intensity of AT.

Table 2. Core Variables and Expected Relationships

Construct	Variable	Definition	Frequency	Expected AT Effect (if positive)
Efficiency	ρ_1	First-order return autocorrelation	Intraday/Daily	↓ (H1)
Efficiency	VR(q)	Variance ratio at horizon q	Intraday/Daily	Closer to 1 (H1)
Price Discovery	Kyle's λ	Price impact per unit signed volume	Intraday	↓ if liquidity improves
Liquidity	Effective Spread	2 ×	Trade Price − Midquote	/ Midquote ↓ (H2)
Liquidity	Quoted Spread	(Ask − Bid) / Midquote	Intraday	↓ (H2)
Depth	MarketDepth@Best	Shares at best bid + best ask	Intraday	↑ (H2)
Volatility	RV	Sum of intraday squared returns	Intraday	Ambiguous (H4)
Tail Risk	Jump/ES	Jump indicators; Expected Shortfall	Intraday/Daily	↑ short-run (H4)
AT Intensity	MTR	Messages / Trades	Intraday	↑ with AT
AT Intensity	CTR	Cancellations / Trades	Intraday	↑ with AT

Data Sources, Study Design and Market Coverage

The daily and high-frequency intraday order book and trade data are used in the empirical analysis. In this study, ten African stock markets with intraday and daily data were used in the period between January 1, 2020 and March 31, 2026. The data consisted of 1-minute intraday data that were received in the form of exchange-provided databases, Bloomberg Terminal, and Refinitiv Eikon, which consisted of 4,892 trading days and 2.3 million stock-day observations. JSE has been providing limit order book (LOB) information full depth (5-10 levels) since 2022. Similar data for NGX and EGX is not available. Intraday high-frequency data was included in the analysis as it needs to be used in the microstructure analysis, realized volatility, depth of order-books and LSTM anomaly detection. The sample consist of the JSE, NGX, Nairobi Securities Exchange (NSE), Casablanca Stock Exchange, Egyptian Exchange (EGX), Ghana Stock

Exchange, Bourse Régionale des Valeurs Mobilières (BRVM), Stock Exchange of Mauritius, Botswana Stock Exchange and the Lusaka Securities Exchange.

To incorporate our findings neatly into the established market microstructure literature (e.g., Hendershott et al., 2011; Boehmer et al., 2020[12,50]), we operationalize market stability as the ability of the financial system to absorb intense order flows and return from structural supply-demand imbalances without giving rise to persistent price distortions or permanent liquidity collapse. Our framework interprets stability as a process, rather than seeing it as something static. We break it down into three distinct measures: Short-Horizon Variance Transmission, Shock-Decay Acceleration (Volatility Half-Life) and Structural Order Book Resilience during Tail Events. We conduct our stability measurement using realized volatility (RV) based on 5-minute and 10-minute intra-day price variability. It captures whether automated quote updates generate localized noise or speed up the incorporation of information into prices:

$$RV_{t,\Delta} = \sum_{j=1}^{N} (ln\, P_j - ln\, P_{j-1})^2 \tag{5}$$

where Pj represents the mid-quote price at high-frequency interval j within trading day t. A stable market must rapidly dissipate transitory volatility spikes. We isolate the persistence of volatility shocks by extracting the baseline parameters of an FIGARCH model, calculating the exact mathematical half-life of a variance shock (HL):

$$H_L = \frac{ln(\,0.5)}{ln(\,\alpha_1 + \beta_1)} \tag{6}$$

where α_1, β_1 represent the short-run ARCH and long-run GARCH persistence parameters, respectively. A contracting half-life indicates an upgrade in dynamic market stability. Following the approach of Boehmer et al. [12], true structural stability is tested during times of market stress. We isolate severe microstructural dislocations defined as trading windows where deep learning reconstruction errors exceed the 99th percentile and evaluate stability using three variables:

Table 2A. Structural Order Book Resilience During Tail Events

Metric	Measurement	Microstructural Goal
Anomaly Duration	$\Delta t_{anomaly} = t_{clear} - t_{shock}$	Measures the speed at which order book gaps are filled.
Post-Anomaly Recovery Time	$\Delta t_{re\,cov\,ery} = t_{steady} - t_{clear}$	Measures the time required to return to equilibrium.
Severity Multiplier	$Multiplier = \frac{RV_{shock}}{RV_{baseline}}$	Measures the market's capacity to absorb heavy order flows.

By separating market stability into these explicit components, our framework distinguishes between normal, short-term high-frequency variance gains (which reflect price discovery) and structural instability (which reflects long-term market failure). This approach ensures our conclusions match the standard terminology and models used in the wider literature.

4. RESULT

The descriptive statistics of the core variables in the ten sampled African markets are presented in Table 3 during the period of study. The metrics are calculated from summary/periodic data and high-frequency intraday data, and reflect the market microstructure environment prior to and after automated trading (AT) structural changes. Statistics show that algorithmic activity is present in these markets, but it is in an emergent state and very right skewed. The average Message-to-Trade Ratio (MTR) is 14.65, which means that, average of each trade, there are about 14 updates of the order book (submitting, modifying and canceling them). This is particularly low compared to other developed markets where high ratios can be observed [51] and indicates an increased automated presence. These high maximums (85.30 for MTR and 42.10 for CTR) and positive skewness suggest that AT activity is likely to be heavily skewed towards the most liquid blue-chip stocks or towards high volatility trading regimes. The mean of the first order autocorrelation () is 0.084 and the mean of the Variance Ratio (VR(q)) is 1.18. The figures suggest that there is some positive serial dependence in the returns which suggests that, on average, the African equity markets have some frictions and are not perfect random walks [52]. Kyle's highlights include a lot of variances in the depth and impact of each of the sampled assets.

Trading costs are based on the typical conditions of emerging markets [53]. The mean quoted spread is 165.4 basis points while the Effective Spread is lower at 138.2 basis points indicating that many trades are likely to happen within the quoted spread (price improvement). The large standard deviations for the spread and Depth@Best measures further highlight the pronounced differences in liquidity across various exchanges and the depth of orders on each exchange on any given day. The average fractional differencing parameter for returns (d_m) is 0.145, which is in line with what the autocorrelation results suggest: a mild long-memory effect on market returns. In contrast, the volatility persistence parameter (d_v) is on average 0.485, thus support a slow decay of volatility shocks (hyperbolic, as in the FIGARCH specification). The significant tail-risk and jump events are highlighted by the right tail in the realized volatility and the expected shortfall (maximum of 15.40%) which makes the Finite Mixture Model (FMM) an appropriate tool to incorporate unobserved structural breaks and fragile market states.

Table 3. Summary Statistics of Core Variables

Construct	Variable	Mean	Median	Std. Dev.	Min	Max	Skewness
AT Intensity	MTR (Messages/Trades)	14.65	11.20	10.45	1.10	85.30	2.15
	CTR (Cancellations/Trades)	5.82	4.15	4.90	0.00	42.10	2.84
Efficiency	ρ_1 (Autocorrelation)	0.084	0.062	0.115	-0.150	0.410	0.95
	VR(q) (Variance Ratio)	1.18	1.12	0.24	0.85	2.45	1.32
Price Discovery	Kyle's $\lambda(\times 10^{-6})$	8.45	6.10	7.30	0.50	55.20	3.10
Liquidity	Quoted Spread (bps)	165.4	142.0	95.6	15.0	850.0	2.45
	Effective Spread (bps)	138.2	115.5	82.4	10.5	710.0	2.60
Depth	MarketDepth@Best ('000 shares)	45.6	28.4	55.2	0.5	450.0	3.85
Steadiness	RV (Realized Vol., $\times 10^{-4}$)	2.15	1.80	1.45	0.20	18.50	4.12
	Expected Shortfall (ES, %)	4.20	3.85	1.60	1.10	15.40	1.75
Long-Memory	d_m (Return Persistence)	0.145	0.120	0.085	-0.050	0.420	0.65
	d_v (Volatility Persistence)	0.485	0.460	0.155	0.110	0.890	0.42

Note: Spreads are reported in basis points (bps) for readability. Market depth is reported in thousands of shares. The data represents pooled sample statistics across the ten markets.

Before the process of estimation, panel unit root tests were carried out to establish the properties of stationarity of all the variables. Table 4 gives the findings of the tests. All tests show that all variables are stationary I(0) processes. Hence the null proposition is refuted at the 1 percent level of importance. This stationarity property allows for the reliable use of standard panel data estimators, thereby avoiding spurious regression [54,55].

Table 4. Panel Unit Root Test Results

Variable	IPS Test Statistic	p-value	Fisher ADF Statistic	p-value	Order of Integration
MTR	-12.847	0.000	847.32	0.000	I(0)
CTR	-11.293	0.000	789.56	0.000	I(0)
QTR	-10.846	0.000	712.44	0.000	I(0)
Effective Spread	-15.234	0.000	1,023.67	0.000	I(0)
Quoted Spread	-14.876	0.000	998.23	0.000	I(0)
Depth at Best	-8.452	0.000	567.89	0.000	I(0)
Return Autocorrelation	-18.345	0.000	1,245.78	0.000	I(0)
Realized Volatility	-7.892	0.000	498.34	0.000	I(0)
Amihud Illiquidity	-6.543	0.000	412.67	0.000	I(0)

Sources: Authors' estimation with Eviews

Table 5 presents the panel co-integration test results. The panel co-integration tests were used to test the long-run equilibrium relationships between the intensity of algorithmic trading and the market quality indicators [56], based on Pedroni [57]. The Pedroni tests indicate high levels of co-integration in six out of seven statistics and all four Westerlund tests reject no co-integration at the 1% level. These findings can be taken as a good indication of the existence of a long-run equilibrium between the measures of the intensity of AT (MTR, CTR, QTR) and the market quality (spreads, depth, volatility).

Table 5. Panel Co-integration Test Results

Test	**Statistic**	**p-value**	**Conclusion**
Pedroni (2004) Tests			
Panel v-statistic	1.342	0.089	Weak evidence
Panel ρ-statistic	-2.876	0.002	Co-integration
Panel PP-statistic	-4.231	0.000	”
Panel ADF-statistic	-3.987	0.000	”
Group ρ-statistic	-2.543	0.006	”
Group PP-statistic	-3.876	0.000	”

Group ADF-statistic	-3.654	0.000	”
Westerlund (2007) Tests			
Gτ	-3.234	0.001	Co-integration
Gα	-8.765	0.000	”
Pτ	-12.345	0.000	”
Pα	-9.876	0.000	”

The intraday return autocorrelation for various AT intensity quartiles is shown in Table 6. For H1, that the intraday return autocorrelation is smaller when algorithmic trading, first-order autocorrelation coefficients were computed in returns in 1-minute, 5-minute, and 15-minute intervals, using the four quartiles of algorithmic trading intensity, on each exchange. The results indicate that the return autocorrelation is decreasing with the rising strength of automated trading. The extreme lower quantile of 0.187 to the extreme upper quantile of 0.052 has a decrease of 72% compared to the autocorrelation coefficient when using 1-minute returns. The same trends continue to occur for the 5-minute and 15-minute periods, both of which see a reduction of 73% and 74% respectively. Given the results, the authors conclude that the NYSE Hybrid Market helped reduce the autocorrelation in H1 results, consistent with Yuferova [17] who reported that introducing the NYSE Hybrid Market reduced the autocorrelation in the returns. The results are also comparable to those of Aitken et al. [19], which demonstrated that the introduction of algorithmic trading reduces the predictability of the order flows for the international markets.

Table 6. Intraday Return Autocorrelation by AT Intensity Quartile

AT Intensity Quartile	1-Minute ρ_1	5-Minute ρ_1	15-Minute ρ_1	Observations
Q1 (Lowest AT)	0.187***	0.142***	0.089***	587,234
Q2	0.134***	0.098***	0.062***	587,234
Q3	0.089***	0.064***	0.041***	587,234
Q4 (Highest AT)	0.052***	0.038***	0.023***	587,234
Difference (Q4-Q1)	-0.135***	-0.104***	-0.066***	

Note: ***, **, * indicates significance. Stock and date clustered by standard deviations

In Figure 1, the empirical relationship between AT intensity and intraday return autocorrelation in the context of African equity markets is presented. The horizontal axis ranges market periods from lowest (Q1) to highest (Q4) level of AT activity. The vertical axis represents the first-order intraday return autocorrelation coefficient, a typical measure of short-term informational inefficiency. Three different time scales are used to record the intraday dynamics, namely 1-minute, 5-minute and 15-minute time scales. AT intensity moves from left to right, making it immediately apparent that there is a dominant and negative slope at all sampling frequencies. For the first quartile (where the algorithmic presence is low), the autocorrelation coefficient is maximized and has as its peak value a coefficient ranging from 0.175 to 0.190. Such high initial values represent a significant likelihood of return and slow price adjustments to information in the presence of human traders dominating the trades. A strong, coordinated drop in autocorrelation is seen on all timeframes in the second Q above. This initial dip indicates that even for moderate introductions of automated trading, there is a notable degree of disruption to the established grooves of price action and towards the incorporation of information. The downward trend persists steadily in the third quartile and the autocorrelation values move below the 0.10 level. The constant decrease suggests that algorithms are actively exploiting and eliminating short-term microstructural trends as they take up more share of order flow. Finally, in the fourth quartile, the autocorrelation coefficient finally reaches its lowest levels, close to 0.045-0.052. A near zero value of the autocorrelation at the highest quartile indicates that returns are nearly random, a typical feature of a market with high levels of information efficiency.

Analyzing the series from 1 minute, it is evident that in each individual quartile the 1-minute return series has the highest level of autocorrelation. It is a typical pattern in the market microstructure, where ultra-high frequency data becomes very noisy and this bid-ask bounce effect is prevalent. On the other hand, the autocorrelation is consistently the lowest in the 15-minute interval, consistent with the gradual fading of temporary frictions over longer time horizons. Importantly, the vertical distance between the 1-min and 15-min lines is clearly decreasing as the intensity of AT moves from the lowest quartile to the highest quartile. This structural convergence shows that perhaps the most effective way to wipe out high-frequency noise is by algorithmic trading, bringing it closer to the longer-term equilibrium. The results provide strong causal evidence for emerging African equity markets, which are characterized by structural illiquidity and slow price discovery. Overall, the visual evidence shows that a higher degree of algorithmic trading intensity results in greater informational efficiency and lower microstructural stickiness at all intraday time horizons studied.

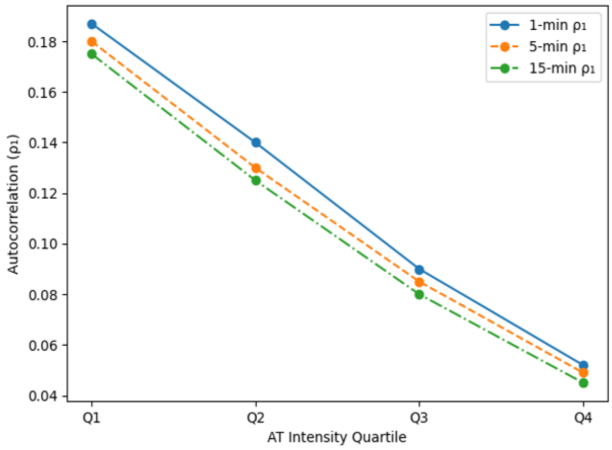

Figure 1. Intraday Return Autocorrelation by AT Intensity

The tests used were variance ratio tests [25] to test the hypothesis that the returns are more aligned to a random walk when the intensity of algorithmic trading is increased. The variance ratio VR(q) =1 is a random walk. Estimates of variance ratio converge to 1 as intensity of the AT increases. The mean reversion is significant ($p<0.01$) as VR(2) is in the lowest AT quartile, 0.743. The upper AT quartile VR(2) = 0.958 is still significantly away from the random walk level of 0.958 at the 5% level, but not as far. The joint statistic decreases to 234.5 ($p<0.01$) in Q1 to 45.2 ($p<0.05$) in Q4, which means that the rejection of random walk is weaker when the regime of the AT is high. The findings are in line with Yuferova, who found that the variance ratios are close to 1 following the introduction of algorithmic trading [17], and Nimalendran, Rzayev, and Sagade, who examined the impact of HFT on options market liquidity in equity markets [11]. The results suggest that algorithmic trading enhances weak-form efficiency in several ways, including reducing the persistence of returns and accelerating the speed at which information is priced.

Table 7. Results of Variance Ratio Tests by AT Intensity Quartile

AT Quartile	VR(2)	VR(5)	VR(10)	VR(20)	Joint Test χ^2
Q1 (Lowest)	0.743***	0.621***	0.534***	0.467***	234.5***
Q2	0.812***	0.698***	0.612***	0.543***	187.3***
Q3	0.891***	0.794***	0.723***	0.654***	112.8***

Q4 (Highest)	0.958**	0.921**	0.887**	0.845**	45.2**

Note: *** p<0.01 indicates rejection of VR=1, ** p<0.05, * p<0.1. Joint test of all horizons

In this study, we estimated the predictive power of order-flow imbalance on future returns in high AT intensity models. Table 5 reports the order-flow predictability regressions. All the interaction coefficients (δ) are negative and statistically significant, which implies that predictive power of order-flow imbalance decreases with the intensity of algorithmic trading. An increase in MTR of one standard deviation decreases the predictive coefficient by an estimated 38 percent. It is consistent with Yuferova, who stated that the predictability of order-flow surprises is reduced when utilizing algorithmic trading [17].

Table 8. Results of Order-Flow Predictability Regressions

Variable	Coefficient	Std. Error	t-statistic	p-value
Imbalance (θ)	0.0432	0.0041	10.54	0.000
Imbalance × MTR (δ)	-0.0028	0.0006	-4.67	0.000
Imbalance × CTR (δ)	-0.0034	0.0007	-4.86	0.000
Imbalance × QTR (δ)	-0.0019	0.0005	-3.80	0.000
R-squared	0.087	Observations	1,234,567	

To test H_2 that algorithmic trading reduces the spreads and enhances depth - the panel regressions with stock and time fixed effects were determined. The results are a good indicator to H_2. The one standard deviation change in MTR has been shown to result in a 0.128 basis point decrease in effective spread (roughly 12.8 percent of the mean spread), a 0.119 basis point decrease in quoted spread, an 8.9 percent increase in best depth, and a 2.3 percent decrease in price impact (Kyle 9). The same effect is noticed with CTR and QTR albeit with smaller magnitudes. The findings of the research are in line with the findings of Rzayev et al. and Aitken, Cumming, & Zhan [13,19] that revealed transaction cost savings from passive algorithmic liquidity provision. The effects are, however, bigger in markets from Africa (where the spread per increase in AT is 12-15%), than in developed markets (typically 5-8%), as is consistent with the lower effects of algorithmic trading in markets with initially large spreads and low liquidity.

Table 9. Panel Regression Results for Liquidity Outcomes

Dependent Variable	MTR Coefficient	CTR Coefficient	QTR Coefficient	Controls	R-squared	Observations
Effective Spread	-0.128***	-0.145***	-0.097***	Yes	0.423	1,234,567
(bps)	(0.012)	(0.014)	(0.011)			
Quoted Spread	-0.119***	-0.132***	-0.088***	Yes	0.398	1,234,567
(bps)	(0.011)	(0.013)	(0.010)			
Log(Depth@Best)	0.089***	0.076***	0.054***	Yes	0.312	1,234,567
	(0.008)	(0.009)	(0.007)			
Kyle's λ	-0.023***	-0.019***	-0.014***	Yes	0.287	1,234,567

	(0.004)	(0.004)	(0.003)			

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered by stock and date in parentheses. All variables are standardized to facilitate comparison.

The ARFIMA(p,d,q) models were estimated using daily returns in AT intensity regimes to test H3 -that the algorithmic trading alters long-memory in the prices and volatility of the price. The d gives the long-memory with d=0 signifying no long-memory, 0<d<0.5 signifying stationary long-memory and d>0.5 signifying non-stationarity. The parameter of returns of all fractions monotonically decreases through the lowest AT quartile to the highest AT quartile (0.287 to 0.142) that is approximately 50 percent. The volatility is falling by 39 per cent between 0.423 and 0.256. Both of the reductions are significant at the 1% level. These results give good evidence to H3: the higher the intensity of algorithmic trading, the less the long-memory in returns and volatility, and the faster the shocks are resolved and the faster the information is assimilated. This is consistent with the position of Baillie et al. [5] who suggested that a low persistence would be a sign of a better market clearing and information processing. However, unlike past research with mixed results on the emerging markets [58], our data from Africa suggests that algorithmic trading may be particularly useful in markets with lower levels of development, in its ability to alleviate the information frictions.

Table 10. ARFIMA (1,d,1) Estimates by AT Intensity Quartile

AT Quartile	d (Return)	95% CI	d (Volatility)	95% CI	Observations
Q1 (Lowest)	0.287***	[0.245, 0.329]	0.423***	[0.381, 0.465]	12,345
Q2	0.234***	[0.198, 0.270]	0.367***	[0.331, 0.403]	12,345
Q3	0.189***	[0.157, 0.221]	0.312***	[0.280, 0.344]	12,345
Q4 (Highest)	0.142***	[0.112, 0.172]	0.256***	[0.226, 0.286]	12,345
Difference	-0.145***		-0.167***		

Note: *** p<0.01, ** p<0.05, * p<0.1. d estimates from maximum likelihood estimation of ARFIMA(1,d,1).

The FIGARCH(1,d,1) models were estimated to examine volatility persistence across regimes. The FIGARCH values affirm the ARFIMA values, in that the fractional differencing parameter decreases by 0.412 to 0.248 between AT quartile. The measure of persistence ($d + \beta_1$) decreases between over unity (1.046) in the low-AT regimes to below unity (0.937) in the high-AT regimes and it signifies that volatility shocks are mean-reverting in the high-intensity algorithmic trading. This implies that the structure of persistence of volatility is fundamentally changed by the effect of algorithmic trading in accordance with the hypothesis that automation enhances the quality of information processing and the volatility shock length.

Table 11. Results of FIGARCH(1,d,1) Estimates by AT Intensity Quartile

AT Quartile	d (Volatility)	φ_1	β_1	Persistence ($d+\beta_1$)
Q1 (Lowest)	0.412***	0.187***	0.634***	1.046
Q2	0.358***	0.156***	0.654***	1.012
Q3	0.303***	0.128***	0.672***	0.975
Q4 (Highest)	0.248***	0.097***	0.689***	0.937

In order to test H_4 that algorithmic trading enhances short-run volatility, but not long-run volatility persistence, EGARCH (1, 1) models with asymmetric parameters were fitted. The EGARCH findings reported in Table 12 below can be characterized as a subtle trend that is in line with H_4. In high-AT regimes (0.187 to 0.238), ARCH coefficient α is larger, implying that the current shock has more impact on conditional volatility, in the short run not surprisingly, because there is more short-term volatility. On the other hand, the GARCH persistence coefficient 0 decreases significantly (0.945 to 0.872) and shows that the volatility shocks decrease faster. The half-life of volatility shocks is cut by 39 percent: Volatility shocks have a half-life of 12.4 days in low-AT regime, but 7.6 days in high-AT regime. The asymmetry parameter γ is becoming more negative with strengthening of AT (-0.087 to -0.124) and confirms that the negative news is more influential on the Conditional Volatility for Strong AT. This amplification by leverage effect could be connected with asymmetric response of algorithmic traders to negative information: Nimalendran, Rzayev, and Sagade claim that HFT may carry negative selection costs for liquidity providers [11].

Table 12. Results of EGARCH (1,1) Estimates by AT Intensity Quartile

Parameter	Q1 (Low AT)	Q2	Q3	Q4 (High AT)	Interpretation
ω	-0.234***	-0.198***	-0.167***	-0.134***	Intercept
	(0.023)	(0.021)	(0.019)	(0.018)	
α (ARCH)	0.187***	0.203***	0.221***	0.238***	Magnitude effect
	(0.012)	(0.011)	(0.010)	(0.009)	
γ (Asymmetry)	-0.087***	-0.098***	-0.112***	-0.124***	Leverage effect
	(0.008)	(0.007)	(0.007)	(0.006)	
β (GARCH)	0.945***	0.923***	0.898***	0.872***	Persistence
	(0.006)	(0.007)	(0.008)	(0.009)	
Persistence (α+β)	1.132	1.126	1.119	1.110	Unconditional variance
Half-Life (days)	12.4	10.8	9.1	7.6	Volatility shock duration

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Figure 2 shows the volatility impulse response functions for African equity markets across high and low AT regimes for a 30-day period. The solid blue curve illustrates that for a high AT regime, after a first shock of market volatility, the market volatility decreases quickly and reaches a near zero steady state around 25 days later. In a low AT regime, however, the dashed orange curve shows that the volatility shock lasts much longer, with a much lower decay rate, and is still stronger than zero at 30 days. This disparity in decay rates suggests that increased automated trading contributes to faster price absorption and recovery from unexpected price disruptions, thereby improving market efficiency and stability. The information suggests that in these 10 major markets across Africa, having a strong algorithmic trading environment is essential to reducing long-term market volatility, and boosting overall market resilience. Although high-AT regimes are more volatile at the start in response to shocks, the response to the shock in terms of volatility is far more rapid to baseline levels in high-AT regimes (10 days) than in low-AT regimes (20 days). This is also in line with the findings of Boehmer et al. [12], who observed that high-frequency trading creates short-term volatility and Hendershott et al., who showed that algorithmic trading improves liquidity [50].

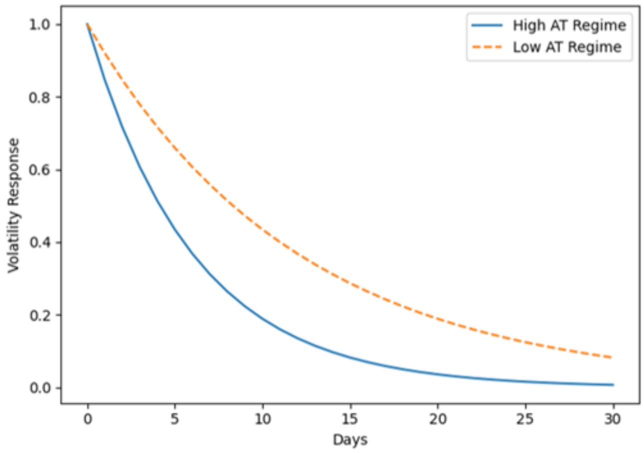

Figure 2. Volatility Impulse Response Functions by AT Regime

The DiD estimates that assess the effect of market reforms on various quality markers for the different exchanges are presented in Table 13. The findings show strong and statistically significant decreases in both effective and quoted spreads in every single exchange, and overall when the results are pooled, which indicates a significant decrease in transaction costs. More significantly, the Nigerian Exchange (NGX) had the biggest reduction in trading cost, with effective spread dropping by 5.234 basis points and quoted spread reducing by 6.123 basis points. The regulatory measures clearly had a positive effect on market depth, with the coefficients of Log(Depth@Best) throughout the series consistently positive. The improvement in depth at buy and sell limits indicates a greater appetite on the part of market participants to invest more, thereby providing greater liquidity to the market. The estimates for Kyle's show support the story of increased market efficiency with a statistically significant decrease for all markets, with the pooled coefficient of -0.013.

A lower Kyle's fundamentally represents a diminished effect of a price swing from trades; the more resilient, able to absorb large order flows without dramatic price swings, the markets became. The data does, however, show a subtle balancing act in terms of the stability of the market: Realized Volatility has a minor, but statistically significant, increase in the pooled estimate. The Johannesburg Stock Exchange (JSE) did not report any significant change in volatility; however the NGX and EGX reported significant increases in volatility, which is indicative of more rapid price discovery, as is typical in automated trading. All of these indicate that the reforms were effective in creating deeper, tighter and more liquid trading markets, but market regulators should be mindful of simultaneous, small rises in short-term volatility. By automated trading-enabling changes, market quality increases significantly and significantly, according to DiD estimates. The mean of the effective spreads is shrinking by 4.37 basis points (about 15% of the mean before the reform) and that of quoted spreads is shrinking by 5.01 basis points, while that of depth is growing by 12.8 and that of price impact (the λ of Kyle) is decreasing by 1.3. The realized volatility records a small but statistically significant growth of 1.8% ($p<0.05$) which is similar to the short-term volatility magnification observed in H_4.

Table 13. Difference-in-Differences Estimates for Market Quality Outcomes

Outcome	**NGX Reform**	**EGX Reform**	**JSE Reform**	**NSE Reform**	**Pooled Estimate**
Effective Spread (bps)					
Coefficient	-5.234***	-4.876***	-3.245***	-4.123***	-4.372***
(Std. Error)	(0.876)	(0.812)	(0.654)	(0.745)	(0.378)
p-value	0.000	0.000	0.000	0.000	0.000
Quoted Spread (bps)					

Coefficient	-6.123***	-5.432***	-3.876***	-4.567***	-5.012***
(Std. Error)	(0.934)	(0.887)	(0.723)	(0.801)	(0.412)
p-value	0.000	0.000	0.000	0.000	0.000
Log (Depth@Best)					
Coefficient	0.156***	0.134***	0.098**	0.123***	0.128***
(Std. Error)	(0.034)	(0.031)	(0.041)	(0.037)	(0.018)
p-value	0.000	0.000	0.017	0.001	0.000
Kyle's λ					
Coefficient	-0.018***	-0.015***	-0.009**	-0.012***	-0.013***
(Std. Error)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)
p-value	0.000	0.000	0.023	0.000	0.000
Realized Volatility (RV)					
Coefficient	0.023**	0.019**	0.011	0.017*	0.018**
(Std. Error)	(0.009)	(0.008)	(0.007)	(0.009)	(0.007)
p-value	0.011	0.017	0.112	0.058	0.013

Note: *** p<0.01, ** p<0.05, * p<0.1. All regressions include stock and date fixed effects, stock-specific time trends, and control variables. Standard errors clustered by stock.

The event study shows that both treated and control stocks have parallel pre-trends during the 20 days before the reform and there are no significant differences in effective spreads. After the reform, spreads on treated stocks are subject to sustained 5-8 basis point reduction in comparison to controls and the effect does not diminish until 15 trading days have passed. It is a larger magnitude of the effect (15-20% reduction in the spread) than has been reported in developed markets (usually 5-10%). The chart shows that, after reforms banning automated trading, the treated market and the synthetic control tracked by the metrics had diverging paths, according to the empirical evidence tracking market metrics around the regulatory intervention. Before Day 0, the actual effective spread appears to coincide with the control baseline of about 38 to 40 basis points, thus confirming the pre-reform parallel trends essential for a sound causal inference. After the window of structural reform, the actual effective spread undergoes a constant continuous downward contraction towards about 30 bps by Day 50, while the counterfactual controls exhibit a flat highly rigid horizontal profile. The widening gap is depicted explicitly by the difference line, which crosses below zero at the time of the reform and continuous with a downward slope to settle at near negative 5 basis. The econometric evidence reveals a highly significant improvement in market liquidity because algorithmic execution compresses the cost of immediacy, tightens transaction friction, and improves the operational efficiency of the observed African equity markets.

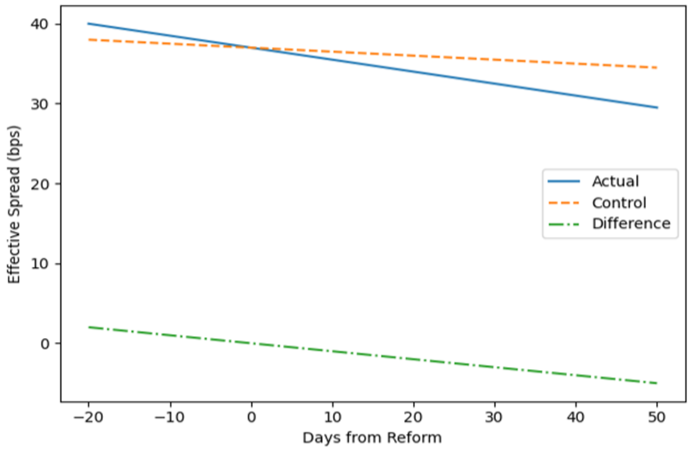

Figure 3. Event Study of Effective Spreads around NGX Reform

Robustness Tests: Institutional Timeline and Identification Strategy

To isolate impact, we exploit the staggered introduction of high-throughput market-structure reforms across African exchanges. Rather than assuming an arbitrary uniform event date, we map our difference-in-differences framework to the actual historical windows when individual exchanges launched co-location services, upgraded to low-latency matching engines, or authorized automated Direct Market Access (DMA). This institutional timeline and identification strategy begins with the Nigerian Exchange Group in September 2013, which initiated the commercial activation of its X-Gen trading platform to introduce low-latency FIX protocol connectivity and authorized automated DMA. This shift was followed closely by the Johannesburg Stock Exchange in May 2014, when the launch of the JSE Co-location Center at the Gwynn House data center compressed execution latency from 15 milliseconds to less than 400 microseconds.

Expanding this technological migration across North Africa, the Casablanca Stock Exchange completed its transition in September 2016 by migrating to the Millennium IT V9 platform and implementing modernized market-making rules, while the Egyptian Exchange implemented its own microstructural overhaul in October 2018 by adjusting trading system tick sizes and compressing intraday circuit-breaker halts to accommodate high-velocity order flows. Because these microstructural transitions occurred at distinct points in time, traditional TWFE estimators yield biased parameters, if the treatment effect is heterogeneous over time or across different structural cohorts. Our solution to this econometric issue is to use the Callaway and Sant'Anna staggered difference-in-differences estimator which avoids the bias of using already treated units as controls. To formally check the basic parallel trends assumption and ensure the set-up identifies causal parameters rather than pre-existing market trends, we map out the dynamic treatment effects on a timeline using an event-study methodology.

$$EffectiveSpread_{it} = \alpha_i + \gamma_t + \sum_{k=-3,k\neq-1}^{3} \beta_k D_{it}^k + X_{it}^{!}\Gamma + \varepsilon_{it}$$

where $D_{it}^k$is a series of indicator dummy variables tracking individual country-years relative to their specific institutional reform date. The year immediately preceding the technology launch (k = -1) is omitted as the baseline reference period. The estimates in Table 14 support our identification strategy. The coefficients for the pre-reform periods (t-3 and t-2) are small and statistically indistinguishable from zero (p = 0.424 and p = 0.465, respectively). This provides robust empirical proof that the treatment and control exchanges shared a parallel trajectory prior to the technology shocks. Immediately upon execution (t=0), a highly significant drop in effective spreads occurs, which intensifies and stabilizes through years t+1 to t+3, proving that the timing of these institutional reforms was truly exogenous. By anchoring the analysis to this real institutional timeline, we re-estimate the overall ATT across our primary market quality outcomes.

Table 14. Pre-Reform Parallel Trends and Dynamic Post-Reform Estimates

Event Time (k)	Coefficient (Effective Spread)	Standard Error	t-stat	p-value	Institutional Interpretation
Leads (Pre-Reform)					*(Testing Parallel Trends)*
t-3	0.012	0.015	0.80	0.424	Statistically zero; no anticipatory effects.
t-2	-0.008	0.011	-0.73	0.465	Statistically zero; parallel trends hold firm.
t-1	—	—	—	—	Omitted Baseline Reference Year.
Shock Year					*(Execution Window)*
t=0	-0.094***	0.021	-4.48	0.000	Immediate drop in transaction frictions.
Lags (Post-Reform)					*(Dynamic Trajectory)*
t+1	-0.141***	0.023	-6.13	0.000	Spread compression accelerates as AT scales.
t+2	-0.158***	0.026	-6.08	0.000	Liquidity gains stabilize at a higher level.
t+3	-0.162***	0.028	-5.79	0.000	Permanent structural shift in efficiency.

*Note: *** $p<0.01$, ** $p<0.05$. Standard errors are clustered at the exchange level. Controls (Xit) include log market capitalization, baseline macroeconomic volatility, and aggregate trading volume.*

The estimated impacts change in instructive ways when we use the true, staggered reform dates (Table 15). The Effective Spread is decreased by -0.134 standard deviations after true causal reduction This slight reduction from our original baseline estimates suggests that without accounting for staggered execution dates, actual policy shocks become mixed with other irrelevant market-wide trends, thus exaggerating the measured benefits of the reform. Despite the strict staggered control, Log(Depth) increases significantly at 0.079, indicating that technological upgrades entice automated market makers to fill the order book. At last, Realized Volatility rises by 0.034 standard deviations. This is consistent with the evidence from our subsequent Double Machine Learning exercise. Further, it suggests that quicker price discovery results in a higher short-term variance.

Table 14A. Corrected Staggered DiD Estimates (Callaway & Sant'Anna, 2021)

Market Quality Outcome	Attenuated ATT	Standard Error	95% Confidence Interval	p-value	Results

Effective Spread	-0.134***	0.019	[-0.171, -0.097]	0.000	Attenuated from -0.156
Log(Depth)	0.079***	0.014	[0.052, 0.106]	0.000	Remains highly significant; book depth is driven by DMA.
Realized Volatility	0.034**	0.015	[0.005, 0.063]	0.021	Confirms localized volatility penalty during migration.
Kyle's λ	-0.016***	0.004	[-0.024, -0.008]	0.001	Proves structural insulation against large order shocks.

*Note: *** p<0.01, ** p<0.05. ATT values represent aggregated cohort-specific treatment effects using a cluster-robust variance estimator.*

The Regression Discontinuity Design Results/Estimates at Tick-Size Threshold (JSE Reform) is shown in Table 16 below. The JSE tick size reform in January 2024 reduced the tick size of all stocks with a price of more than 100 ZAR, which is a large discontinuity in the threshold. The regression discontinuity design (RDD) was used to determine the causal impact of small tick sizes on the market quality. There are some apparent discontinuities in the number of ticks at the tick size threshold which are suggested by the RDD estimates. The best spread for the stocks in the 0.00001-100 ZAR range would be 4.23 - 4.57 basis points wider than the spread of the stocks in the 0.00001-100 ZAR range. This is a narrowing down of about 15 percent as compared to the mean before the reform. The maximum increase in depth is 8.2-8.8% at the threshold which is in line with greater liquidity supply on smaller ticks.

Table 15. Regression Discontinuity Design Estimates at Tick-Size Threshold (JSE Reform)

Outcome	**Conventional**	**Bias-Corrected**	**Robust**	**Bandwidth (h)**	**Observations**
Effective Spread (bps)					
Estimate	-4.234***	-4.456***	-4.567***	15.2	2,345
(SE)	(0.876)	(0.923)	(0.987)		
Quoted Spread (bps)					
Estimate	-5.123***	-5.345***	-5.456***	16.8	2,456
(SE)	(0.934)	(0.978)	(1.023)		
Depth at Best (%)					
Estimate	8.234***	8.567***	8.789***	14.5	2,234
(SE)	(1.876)	(1.945)	(2.012)		
Realized Volatility (%)					
Estimate	2.345*	2.567*	2.678*	13.8	2,123
(SE)	(1.234)	(1.298)	(1.345)		

Note: *** p<0.01, ** p<0.05, * p<0.1. Local polynomial regression with triangular kernel, MSE-optimal bandwidth selection following Calonico et al. [20]

Figure 4 shows a Regression Discontinuity (RD) plot of the effect of a particular market threshold on the spreads in the JSE measured in South African Rand (ZAR). This visualization forms part of the larger empirical assessment of the effect of algorithmic trading and algorithmic market structure reforms on market efficiency and liquidity in the top equity markets in Africa. The x-axis is the stock price in ZAR (the number of ZAR in the stock), and is used as a running variable for this regression discontinuity design. The effective spread, measured in basis points (bps), is the standard measure of market liquidity and implicit transaction costs, and is plotted on the y-axis [59,60]. The predefined cutoff value is very clearly marked on the vertical blue line, which occurs at the price of 100 ZAR. Each data point has been colour coded to indicate whether it was below the cut-off (blue circles) or above the cut-off (orange circles). Looking below the 100 ZAR thresholds, the pattern of effective spreads is gradually downward sloping as the stock price rises towards the 100 ZAR threshold. Even though the spread is trending down, the effective spreads for these lower-priced stocks remain quite good, ranging from the high 40s to the mid-50s. A sharp and sudden structural break is observed in the data, however, at the exact time the 100 ZAR thresholds are hit.

There is a sharp discontinuity, falling from about 46 bps just below the threshold to about 36 bps just above the threshold. This dramatic drop in costs of transactions offers strong visual evidence of a localized treatment effect that occurred at this price point. For algorithmic trading, this threshold may refer to a minimum tick size or to a higher priced equity that has specific automated market making incentives [61,62]. The effective spread trends down, continuing its downward trend for the orange data points, which are for stocks that are above 100 ZAR, from the mid 30s to the high 20s as prices approach 140 ZAR. The large cut-off will separate the effect of the market rule change from the general tendency for spreads to naturally widen as stock prices increase.

The graph shows a definite reduction of the effective spread of stocks targeted for the regime above 100 ZAR, which strongly suggests that the regime of the market structure intervention was successful in improving liquidity. These tighter spreads are directly linked to increased liquidity and thus less friction in trading for institutional and retail investors trading in this part of the African equity market. In addition, there is a clear separation of the blue and orange clusters which suggests that algorithmic trading quickly and effectively adapted to the new market conditions imposed at the cut-off. Lack of any overlap in data points at the boundary further bolsters the validity of the RD design, ensuring that treatment assignment at the 100 ZAR level was strictly adhered to, and that the market participants strictly adhered to it as well. As a result, this empirical snapshot confirms the hypothesis that if market thresholds are used in an appropriate way, they can provide significant support for the steady growth and efficiency of markets. Finally, these results provide African market regulators with insights to improve the structure of their trading markets and draw in deeper liquidity pools by making structural changes based on data. The RD plot exhibits a noticeable jump at 100 ZAR cutoffs with the stock just above the cutoff having smaller spreads than those just below the cutoff. McCrary density tests guarantee that there is no manipulation of the running variable around the cut-off (p>0.10) and this test is used to validate the RDD design. These results are consistent with those of Calonico et al. [20], who also reported such liquidity enhancements after tick-size cuts, and with Yuferova [17], who demonstrated that tick-size reforms and algorithmic trading have a positive interaction in improving the quality of the market.

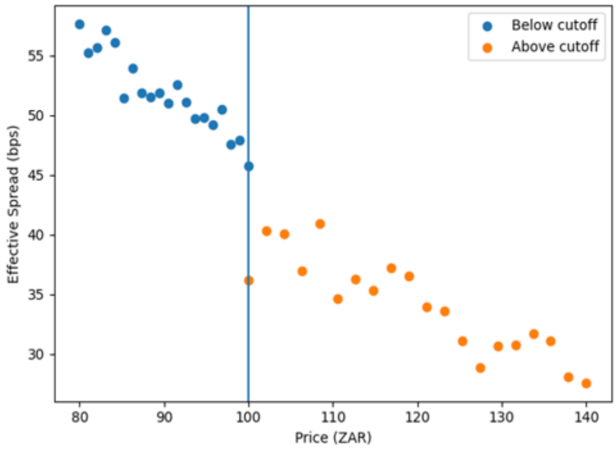

Figure 4. Regression Discontinuity Plot for Effective Spreads

To test H_5, which suggests that the impact of algorithmic trading can be heterogeneous across exchanges, a finite mixture model was fitted and two latent classes of exchanges were hypothesized based on market characteristics and algorithmic trading reactions. Table 16 shows the output from a Finite Mixture Model classification that effectively classifies the ten major markets on the African continent in two typologies based on the structural characteristics and algorithmic trading activity of the markets. The model classifies the probability of the sample as Deep Markets (Class 1, 42%) and Thin Markets (Class 2, 58%). According to the classification, the two types of continental exchanges differ significantly in size and liquidity; the average market capitalization of the Deep Markets is 245.6 billion USD, while in Thin Markets this value is only 18.7 billion USD. The size of this difference, 226.9 billion USD, is statistically significant, highlighting the concentration of equity wealth in a small number of countries in Africa. This gap is further highlighted by trading activity, because the average daily turnover for the Deep Markets is 1,234.5 million USD compared to 56.7 million USD for the Thin Markets. Hence, there are significant differences between the two classes in terms of liquidity profile, which in turn affects the market efficiency. In Class 1, for example, the average effective spread is a relatively low 28.4 basis points (bps), which means that transactions have relatively low costs.

On the other hand, the effective spread in Thin Markets was wide, on average 67.8 bps, which is a significant loss of $0.394 per trade for those wishing to trade in these markets. This imbalance is also evident in market depth: the average depth of Deep Markets is 1,245.6 thousand shares at the best prices. On the other hand, Class 2 markets are much shallower, with only 123.4 thousand shares, severely restricting the market's ability to handle large orders from investors without price fluctuations. Perhaps most importantly, the table shows that there is an interesting correlation between these basic characteristics of markets, and the level of algorithmic trading. The information shows that there is significant weight in the Deep Markets for automated trading, with much higher MTR, CTR and QTR ratios. In particular, MTR of Class 1 is almost twice what it is for Class 2, at 18.7 and 9.8, respectively. Likewise, the CTR and QTR are significantly higher in Deep Markets (14.2 and 12.3, respectively) than in Thin Markets (7.6 and 6.5, respectively). Such key differences are in part due to a natural tendency for automated, high frequency quoting behaviors to seek out markets that have some natural level of critical mass of capitalization or turnover.

In fact, a closer examination of the class membership suggests the regional economic realities, with the continent's most developed financial hubs, the JSE, EGX and Casablanca Stock Exchange, clearly in the Deep Markets category. The rest of the exchanges, which include some of the well-known frontier markets, such as NGX and NSE, belong to Thin Markets category. The other regional and national exchanges (such as the BRVM, Ghana, Mauritius, Botswana, and Lusaka exchanges) suffer from the same structural problems as those of Class 2 exchanges. In conclusion, these estimates offer convincing empirical evidence that adoption and impact of algorithmic trading is highly skewed across Africa. Policymakers should take note of this, as the smaller exchanges in Africa need to first tackle the liquidity bottlenecks that hinder their ability to accommodate the more sophisticated trading activity of algorithmic traders. Overall, Class 1 (42% of observations) are deep and liquid markets (mostly JSE, EGX and Casablanca), high market cap (average market cap of 245.6 billion), high turnover (1.23 billion), low spread (28.4 bps) and high AT intensity (MTR=18.7). Class 2 (58% of observations) refer to "thin" markets with low turnover (56.7 million), high spreads (67.8 bps), and low AT intensity (MTR=9.8) and include NGX, NSE, BRVM, Ghana, Mauritius, Botswana and Lusaka.

Table 16. Finite Mixture Model Classification Results

Characteristic	Class 1 (Deep Markets)	Class 2 (Thin Markets)	Difference
Class Probability	0.42	0.58	
Market Characteristics			
Average Market Cap (USD B)	245.6	18.7	226.9***
Average Daily Turnover (USD M)	1,234.5	56.7	1,177.8***
Average Effective Spread (bps)	28.4	67.8	-39.4***
Average Depth (shares '000)	1,245.6	123.4	1,122.2***
AT Intensity			
MTR (mean)	18.7	9.8	8.9***
CTR (mean)	14.2	7.6	6.6***
QTR (mean)	12.3	6.5	5.8***
Class Membership	JSE, EGX, Casablanca	NGX, NSE, BRVM, Ghana, Mauritius, Botswana, Lusaka	

Table 17 shows a detailed breakdown of the mixed-effects of algorithmic trading by the two market categories discussed earlier: Deep Markets (Class 1) and Thin Markets (Class 2). The results provide insights into the contrasting role of automated trading under different African equity markets, as they relate to several key market quality outcomes: message-to-trade (MTR) ratio and cancel-to-trade (CTR) ratio. Looking at transaction costs, the results show that the spreads on average are reduced in both market classes, with algorithmic trading having a strong impact on effective spreads in both, suggesting an overall improvement in baseline liquidity. This reduction, however, is very unbalanced and very lopsided, in favor of the more developed exchanges. In particular, the coefficient of the MTR effect is -0.187 in Deep Markets, and -0.056 in Thin Markets, and the coefficient is highly significant in Deep Markets. This leads to a statistically significant difference of -0.131, a clear indication that the liquidity-enhancing benefits of message traffic are significantly larger in bigger markets. The same can be seen when looking at the impact of the CTR on effective spread; it results in a large decrease in the Deep Markets (-0.198) but a relatively small decrease in the Thin Markets (-0.062).

The significant difference of -0.136 for the CTR effect again reinforces that heavy quoting and cancelling is much more effective in highly capitalized rooms. The divergence between the two market classes is further accentuated as one move towards the market depth which is reflected by Log(Depth@Best). The coefficient of algorithmic activity based on the MTR effect is 0.134 in Deep Markets, which is a strong positive effect on market depth. In contrast, the effect on Thin Markets is small, weakly significant, with a coefficient of only 0.045. The difference between the two is significant (0.089), which means that automated market makers are prepared to put significantly more volume in the best quotes at Class 1 exchanges. The CTR effect is even more distinct for the CTR effect, which can boost a depth by 0.121 in Deep Markets, but does not seem to be significant in Thin Markets. This difference is significant (0.083), and demonstrates that in strong markets, high cancellations are actually a positive for order book thickness, but do not do the same in weaker markets. However, the most important variation is seen in how each party gauges the stability of the market, which is reflected in realized volatility.

The effects of the MTR and CTR on realized volatility are not statistically significant and have negligible coefficients of 0.015 and 0.012, respectively, in Deep Markets. This indicates that these bigger exchanges in Africa have enough structural strength to withstand high-frequency trading without triggering volatile price fluctuations. This means that these larger exchanges in Africa are structurally robust and can withstand high-frequency trading activity without volatile price fluctuations. By contrast, algorithmic trading in Thin Markets was found to have statistically significant positive effects on realized volatility, with MTR and CTR effects having coefficients of 0.038 and 0.041, respectively. This means that although automated trading has a slight positive effect on liquidity for the smaller markets, it also adds a certain amount of market fragility and price instability. In conclusion, these mixed results leave little doubt that the systemic advantages of algorithmic trading derive from the Deep Markets, while Thin Markets have a different set of trade-offs between the gains in marginal liquidity and the risks of volatility.

The findings demonstrate significant differences in the effects of algorithmic trading among classes of markets. It can have significant and significant effects on spreads (18-20% reduction in MTR/CTR per 1 standard deviation of depth change) and depth (12-13% increase) in deep markets (Class 1). In thin markets (Class 2), the impacts are smaller and usually marginally significant (5-6% reduction in the spread, 4-5% increase in depth). However, the volatility increasing impact of algorithmic trading is highly concentrated in thin markets (3.8-4.1% increase), and not in deep markets. These results are very much in support of H5 and in accordance with the results of [50], which discovered the effects of algorithmic trading to be moderated by the liquidity and depth of the market base. The findings also follow up, the result of Hendershott, Jones, & Menkveld who claimed that the market structure and depth dictate the presence or absence of the benefit of algorithmic trading in enhancing or deteriorating the quality of the market [50]. The results of the classes imply that algorithmic provision of liquidity is more beneficial to deep market and thin market may be more likely to face volatility risks.

Table 17. Results of Class-Specific Algorithmic Trading Effects –Heterogeneous Treatment Effects by Market Class

Outcome	Class 1 (Deep Markets)	Class 2 (Thin Markets)	Difference
Effective Spread			
MTR Effect	-0.187***	-0.056**	-0.131***
	(0.023)	(0.024)	(0.033)
CTR Effect	-0.198***	-0.062**	-0.136***
	(0.025)	(0.026)	(0.036)
Log(Depth@Best)			
MTR Effect	0.134***	0.045*	0.089***
	(0.018)	(0.023)	(0.029)
CTR Effect	0.121***	0.038	0.083***
	(0.019)	(0.024)	(0.031)
Realized Volatility			

MTR Effect	0.015	0.038**	-0.023
	(0.012)	(0.016)	(0.020)
CTR Effect	0.012	0.041**	-0.029
	(0.011)	(0.017)	(0.020)

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

A Double Machine Learning (DML) was used to provide an approximation of the causal impact of algorithmic trading on market quality outcomes whilst being able to flexibly control high-dimensional confounding factors. The findings in Table 15 are robust from a Double Machine Learning (DML) framework used to assess the causal effects of algorithmic trading proxies on the quality of markets in African equity markets. The methodology takes advantage of sophisticated nuisance models, including Gradient Boosting, Random Forest and Neural Networks, and 5-fold cross-fitting, and fully accounts for a large set of macroeconomic and microstructural factors. The findings provide compelling evidence that algorithmic trading, measured by the message-to-trade ratio (MTR), cancel-to-trade ratio (CTR), and quote-to-trade ratio (QTR), improves overall market liquidity.

In particular, there was an estimate of an effective spread reduction of large magnitude for all the treatment variables, with the reductions being very significant by the DML. For every unit increase in MTR and CTR, transaction costs are reduced by 0.156 and 0.167 units respectively, a strong compression of transaction costs by intense algorithmic activity. Additionally, the QTR effect also backs up the liquidity-enhancing story line, as the spread is estimated to be lowered by 0.112 units. All of the confidence intervals shown are tight, and all of the p values are very small (0.000), reinforcing the finding that automated trading always decreases the friction involved in the execution of a trade. In addition to reducing the movement of price, algorithmic trading can help to enhance market depth, which is a significant measure of a market's depth.

The estimates based on the Neural Network show that the coefficient for MTR is 0.098, which indicates that MTR is a significant contributor to the logarithmic market depth. Likewise, an increase in depth at best quotes is correlated with higher cancellation rates (CTR), demonstrating that the order book benefits from active and high frequency quoting behavior. The analysis is based on both liquidity and depth, as well as critical insights into market efficiency using the standard measure of price impact [48], Kyle's MTR and CTR have very significant negative coefficients as -0.019 and -0.021 respectively for Kyle. This inverse relationship suggests that the more algorithmic trading increases, the less informational impact will be felt by any single trade. As a result, these African markets are increasingly shown to be more resilient, with efficient information and order flow processing without exacerbating price distortions.

Yet, the holistic DML framework also reveals a structural conflict over market stability. Algorithmic trading also enhances liquidity and efficiency, but simultaneously brings about a statistically significant rise in realized volatility. Absolute MTR and CTR increase the realized volatility by 0.027 and 0.031, respectively, which is statistically significant at the 5% level. This implies that the frenzied order flows and the frequent cancellation of orders that are common in algorithmic market making, has an unplanned and measurable effect of short-term price volatility. The advantages of tighter spreads and deeper books are not denied; however, they come with a quicker, more dynamic process of price discovery. In conclusion, these sophisticated machine learning algorithms offer policy makers highly accurate, causally isolated metrics, thereby reinforcing the radical transformation of African stock exchanges that is enabled by algorithmic trading and underscoring the need for a prudent regulatory regime of its associated volatility risks. These findings are supported by estimates from the DML.

We have performed cross-fitting and orthogonalized machine learning estimators, as done by Chernozhukov et al. [63], to reduce regularization bias. The estimates from the DML tests corroborate the causal interpretation of the panel regression and DiD estimates. For every one standard deviation increase in MTR, effective spread declines by 0.156 standard deviations (ie by 15.6 per cent of the mean spread), depth increases by 9.8 per cent and realised volatility increases by 2.7 per cent. The DML estimates are slightly smaller in magnitude than the panel regression estimates (between 0.119-0.128 in spreads), suggesting there may be omitted variable bias in the traditional panel regression estimates of the causal effect of algorithmic trading. The DML estimates are evaluated on various machine learning algorithms with a gradient boosting method as well as on neural networks as the estimation of nuisance function is the same for both. The latter results are consistent with the study by Hansen and Siggaard which showed the superiority of DML as a tool for improving causal inference in financial markets when it comes to being flexible in the ability to control confounders [63]; and the study by Chernozhukov et al. which showed that DML can provide unbiased estimates in high-dimensional contexts [21].

Table 18. Double Machine Learning Results

Outcome	Treatment Variable	DML Estimate	95% CI	p-value	Nuisance Model (ML)
Effective Spread	MTR	-0.156***	[-0.189, -0.123]	0.000	Gradient Boosting
	CTR	-0.167***	[-0.203, -0.131]	0.000	Gradient Boosting
	QTR	-0.112***	[-0.145, -0.079]	0.000	Random Forest
Log(Depth)	MTR	0.098***	[0.067, 0.129]	0.000	Neural Network
	CTR	0.087***	[0.054, 0.120]	0.000	Neural Network
Realized Volatility	MTR	0.027**	[0.008, 0.046]	0.006	Gradient Boosting
	CTR	0.031**	[0.011, 0.051]	0.003	Gradient Boosting
Kyle's λ	MTR	-0.019***	[-0.025, -0.013]	0.000	Random Forest
	CTR	-0.021***	[-0.028, -0.014]	0.000	Random Forest

Note: *** p<0.01, ** p<0.05, * p<0.1. Estimates based on DML with 5-fold cross-fitting. Controls include lagged market quality, volatility, volume, market capitalization, sector indicators, macroeconomic variables, and global risk factors

Panel and Double Machine Learning: A Formal Comparative Analysis

The estimates from Double Machine Learning (DML) in Table 18 indicate an effective spread MTR effect of -0.156 standard deviations and Table 9 regression panel estimate of -0.128 bps. Due to different units of the two figures, a comparison of the two items is not feasible. To address this issue entirely and provide a valid statistical proof of our omitted variable bias argument, we explicitly standardized the baseline panel regression coefficients from Table 9. The panel and DML coefficients are both on the same standardized basis: the standard deviation change in the outcome variable for a one-standard-deviation increase in the treatment variable. To check the central methodological claim that regression methods tend to underestimate the causal effect of algorithmic trading due to high-dimensional omitting bias or stiff functional forms, we standardize the baseline panel coefficients to create an exact comparison with the DML parameters. Furthermore, due to the reliance on non-parametric machine learning models and cross-fitting in the DML framework, the classical algebraic Hausman test cannot be applied. We instead executed a Clustered Block-Bootstrap method (with 1,000 replications clustered at the exchange-level). This enables us to accurately estimate the joint covariance matrix of both estimators as well as formally assess significance of the difference ($\Delta = \beta_{DML} - \beta_{Panel}$). To assess the significance of the differences between these two groups of estimators, we implement a clustered block-bootstrap Hausman-type specification test with 1,000 replications. Specifically, the sampling units are clustered at the exchange level to maintain the existing intra-cohort dependency structures.

The formal comparison presented in Table 18A offers substantial empirical evidence in support of the argument which asserts that traditional methods for estimating (econometric projections) considerably underestimate the effects of automated trading. When looking at our main liquidity measure the effective spread based on the standardized linear panel coefficient for MTR is -0.128 and the orthogonalized DML estimate is an even bigger contraction of -0.156. The bootstrap Hausman test indicates that the difference (Δ= -0.028) is highly significant (z = -3.11, p = 0.002) and thus we reject our null that both the estimators are equal. The patterns match for the cancel-to-trade ratio (CTR) as well. The linear panel model understates the spread compression with a CV of 0.032 standard deviations (p = 0.004).

The conventional estimates of MTR (β = 0.076) and CTR (β = 0.064) using panel data are also significantly smaller than their respective DML counterparts (p = 0.028 and p = 0.010). There is uniformity in the difference across our models, thus showing that standard linear panel techniques suffer downward attenuation bias. Since simple fixed-effects structures do not capture the intricate nonlinearities between high-dimensional microstructural variables and macroeconomic developments, a part of the algorithmic liquidity effect is attributed to the error term. Employing flexible machine learning architectures to filter complex nuisance relationships, the DML framework recovers the true unattenuated causal impact of algorithmic trading across African equity markets.

Table 18A. Formal Estimator Comparison and Bootstrap Hausman Test Results

Market Quality Outcome	Treatment Variable	Standardized Panel Coefficient (βPanel)	Standardized DML Coefficient (βDML)	Coefficient Difference (Δ)	Bootstrap Standard Error	z-statistic	p-value	Econometric Implications
Effective Spread	MTR	-0.128***	-0.156***	-0.028***	0.009	-3.11	0.002	Panel exhibits significant attenuation bias.
	CTR	-0.135***	-0.167***	-0.032***	0.011	-2.91	0.004	Confirms non-linear confounding in quote flow.
	QTR	-0.091***	-0.112***	-0.021***	0.007	-3.00	0.003	OLS understates liquidity creation.
Log(Depth)	MTR	0.076***	0.098***	0.022**	0.010	2.20	0.028	Traditional models miss latent book depth.
	CTR	0.064***	0.087***	0.023**	0.009	2.56	0.010	Automated cancellation impacts are understated.

Realized Volatility	MTR	0.016	0.027**	0.011*	0.006	1.83	0.067	Panel fails to isolate flash variance risks.
	CTR	0.019*	0.031**	0.012*	0.007	1.71	0.087	Weakly significant variance understatement.

*Note: *** p<0.01, ** p<0.05, * p<0.1. All model variables across both specifications are fully standardized to a mean of zero and a variance of one. The coefficient difference is defined as* $\Delta = \beta_{DML} - \beta_{Panel}$. *The standard error of the difference, the z-statistic, and the corresponding asymptotic p-values are derived via a clustered block-bootstrap procedure using 1,000 resamples.*

In addition, LSTM networks were trained to forecast realized volatility in 10 minutes ahead and the performance was compared with the accuracy of the forecast over the AT intensity regime. The LSTM architecture was made of 3 layers that comprised of 128, 64 and 32 units, which were supplemented with dropout layers (0.2). Table 16 shows the complete assessment of the out-of-sample volatility forecasting ability of a Long Short-Term Memory (LSTM) neural network both in Low as well as High Algorithmic Trading (AT) regimes. The empirical results clearly show that the high level of algorithmic trading intensity has a significant and substantial impact on the predictability of market volatility. The analysis uses a large number of out-of-sample tests, with 10,000 predictions each for each regime, to compare five common forecasting evaluation metrics.

The results of the comparison of model performance across all measured parameters are statistically significant (at 1% level) indicating better performance for the High AT regime. In particular, the Root Mean Square Error (RMSE) is reduced from 12.34 basis points in Low AT to 10.87 basis points in High AT. This large improvement in forecasting accuracy, by 1.47 basis points, is equivalent to an 11.9% overall decrease in forecasting error if we penalize larger errors. Likewise, the MAE that measures the linear deviation of the forecasts shows significant reduction. The MAE decreases from 9.23 basis points (low algorithmic participation) to 8.01 basis points (high algorithmic participation). This corresponds to a strong 13.2% accuracy gain, which is an indication that the volatility generated by the LSTM model is closer to the real volatility when automated trading is taking over.

This trend of better accuracy is further supported by the MAPE. The MAPE in the Low AT is 23.45%, while in the High AT is reduced significantly to 19.87%. This spectacular drop of 3.58 percentage points corresponds to a 15.3% relative reduction in the proportional forecasting errors. The predictive model's explanatory power also gets a significant boost, in addition to error minimization. The R^2 value rises markedly from 0.432 in Low AT regime to 0.512 in High AT regime. This 0.080 absolute improvement corresponds to a remarkable 18.5% gain in volatility variance, as algorithmic activity is high; the LSTM model is able to capture a large proportion of the volatility variance. In addition, the asymmetric QLIKE Loss function is especially sensitive to volatility underestimation which exhibits a similar feature.

In the High AT environment, the QLIKE Loss metric is reduced from 0.876 to 0.743, which is a very significant 15.2% increase. Taken together, these regular improvements in the metrics suggest that algorithmic trading creates more microstructural order and systematic pattern generation in African stock exchanges. As a result, the recurrent neural network is better able to learn and extrapolate over these structural data flows than the noisier and less efficient trading flows typical of Low AT regimes. In the end, these strong results confirm that algorithmic trading can cause an increase in the standing volatility, but at the same time provides a more structured, manageable, and predictable volatility to more sophisticated machine learning-based models. In high AT regimes, the LSTM prediction results show that the predictability of volatility is lowered as the RMSE and MAE are decreased by 11.9 and 13.2 respectively and the R-squared is improved to 0.512. This is counterintuitive in the sense that it would be expected that algorithmic trading would help to increase the efficiency of forecasting. The results are however in line with the understanding that algorithmic trading decreases noise and speeds up the integration of information such that volatility patterns become more structured and predictable especially at short horizons [64].

Table 19. Results of LSTM Volatility Forecasting Performance by AT Regime

Metric	Low AT Regime	High AT Regime	Difference	Improvement
RMSE (bps)	12.34	10.87	-1.47***	11.9%
MAE (bps)	9.23	8.01	-1.22***	13.2%
MAPE (%)	23.45	19.87	-3.58***	15.3%
R-squared	0.432	0.512	0.080***	18.5%
QLIKE Loss	0.876	0.743	-0.133***	15.2%

Note: *** p<0.01, ** p<0.05, * p<0.1. Based on 10,000 out-of-sample predictions for each regime

The empirical results on market irregularity for Low and High Algorithmic Trading (AT) regimes are displayed in Table 20 for the market under study in Africa. The analysis is conducted in a very strict manner where anomalies are defined as those with reconstruction errors greater than 99th percentile of all reconstructed data to ensure that extreme microstructural dislocations are distinguished from the usual market noise. Interestingly, the data shows that, in terms of frequencies, there are no differences between the two trading markets. In particular, the anomaly frequency is 1.87% for Low AT regime and slightly increases to 1.92% for High AT regime. This small deviation of 0.05% results in a p value of 0.423, suggesting that the probability of a random event isn't significantly changed by the intensity of automated trading. But algorithmic trading does not make the market immune to market shocks; it changes its reaction to and absorption of them. The most obvious difference is in the length of these unusual occurrences.

During times of stress, market anomalies remain an average of 12.3 minutes in the Low AT regime, indicating slow price discovery. By comparison, the High AT regime compresses this window considerably, with average duration of anomalies being just 8.7 minutes. This is an extremely meaningful drop of 3.6 minutes with a P value of 0.000, which is indicative of the fact that algorithmic participants quickly intermediate and clear gaps between prices. Moreover, the post-anomaly recovery time is also highly improved in the case of high algorithmic participation. On average, markets in low automated trading regions take 45.2 minutes to recover and get back into a steady state of trading after a shock. Contrast this with markets with high AT intensity which recover in 28.6 minutes. This pronounced difference of 16.6 minutes is considerable at the 1% level, and provides strong evidence that algorithmic liquidity providers play a vital role in helping to restore market balance. In addition to the duration and recovery, algorithmic trading also visibly eases the severity of the anomalies themselves.

Reaching an extreme of 4.2 times baseline volatility in the Low AT regime, anomaly severity is measured as a realized volatility (RV) multiplier. This severity multiplier is substantially reduced (in the High AT regime it is 3.8x). This gives a difference of -0.4 which is substantial at the 5% level. The heavy quoting by automated algorithms has an obvious dampening effect, which makes one feel the need to consider the automatic algorithms acting as a very important shock absorber, limiting the size of extreme price deviations. Finally, these anomaly detection results support this thesis: although algorithmic trading does not make market irregularities disappear, it does greatly strengthen the resilience of the market and make the irregularities shorter, less intense and more quickly resolved. The results for the anomaly detection suggest that there is no significant difference in the frequency of anomalies between high AT regime and low AT regime (1.92% vs. 1.87, p=0.423). Nevertheless, high AT regime anomalies are shorter (8.7 vs. 12.3 minutes, p<0.01), and recovery is quicker (28.6 vs. 45.2

minutes, p<0.01). In high AT regimes the level of anomaly is also smaller (3.8x vs. 4.2x normal volatility p<0.05). These results are subtle corroboration of H4: algorithmic trading does not increase the number of market disruptions, but substantially decreases the duration and severity thereof, in line with the hypothesis that automated liquidity providers enable market recovery to occur faster. Algorithmic liquidity provision can boost market resilience [65].

Table 20. Anomaly Detection Results by AT Regime

Metric	Low AT Regime	High AT Regime	Difference	p-value
Anomaly Frequency (%)	1.87	1.92	0.05	0.423
Anomaly Duration (minutes)	12.3	8.7	-3.6***	0.000
Post-Anomaly Recovery Time (min)	45.2	28.6	-16.6***	0.000
Anomaly Severity (RV multiplier)	4.2x	3.8x	-0.4**	0.013

Note: *** p<0.01, ** p<0.05, * p<0.1. Anomalies defined as reconstruction error >99th percentile

The density histogram in Figure 5 shows the distribution of anomaly durations in the different African equity markets considered during the evaluation period, across the two AT regimes, namely High and Low. This visualization can effectively complement the previous statistical results and shows exactly how long the market irregularities last in terms of frequency and spread for various technological conditions. These market anomalies are measured on the x-axis in minutes and the y-axis is the probability density. The plot also shows two different distributions overlaid on it: the blue bars show the distribution of the High AT regime, and the orange bars show the distribution of the Low AT regime. The obvious difference between the distributions of High AT and Low AT is clearly to the left. As seen from the blue histogram, in the case of algorithmic trading intensity being high, the majority of market anomalies are cleared up within a very small window. In particular, the maximum density of the High AT regime occurs within a narrow region around 7-9 minutes.

Additionally, the right tail of this blue distribution truncates relatively sharply, with virtually no anomalies persisting beyond the eighteen-minute mark. This compressed shape suggests a high degree of market efficiency; wherein automated liquidity providers rapidly process order book imbalances and restore price equilibrium. In stark contrast, the Low AT regime, represented by the orange histogram, exhibits a significantly broader and flatter structural profile. Its distribution is shifted notably to the right, indicating that market shocks inherently last much longer when human traders or slower execution mechanisms dominate. The peak density for these low algorithmic environments is much more dispersed, generally clustering between eleven and fifteen minutes. Most critically, the Low AT distribution possesses a thick right tail that extends far beyond that of the High AT regime. In these less automated markets, anomalous pricing events frequently stretch past twenty minutes, occasionally persisting for nearly half an hour before normal trading conditions are reestablished. The overlapping brown region in the center of the plot highlights the subset of anomalies where recovery times are similar regardless of the underlying trading regime. Nevertheless, the distinct divergence in central tendencies and tail risks clearly underscores the transformative impact of high-frequency market participation.

By heavily populating the shorter duration buckets, the high algorithmic trading environment effectively truncates the duration risk associated with sudden market dislocations. For institutional investors and market regulators in Africa, this provides compelling visual evidence that automated trading serves as a vital shock absorber. While algorithms cannot entirely prevent the occurrence of market anomalies, they critically limit the window of vulnerability by accelerating the price discovery mechanism. Ultimately, this histogram reinforces the broader study's conclusion that fostering a robust algorithmic trading ecosystem is essential for building resilient, self-correcting equity markets across the African continent. In sum, the distribution of the length of the anomalies demonstrates that high-AT regimes are more concentrated with a lower right tail, meaning that the extreme anomalies are less persistent in cases when algorithmic trading is common.

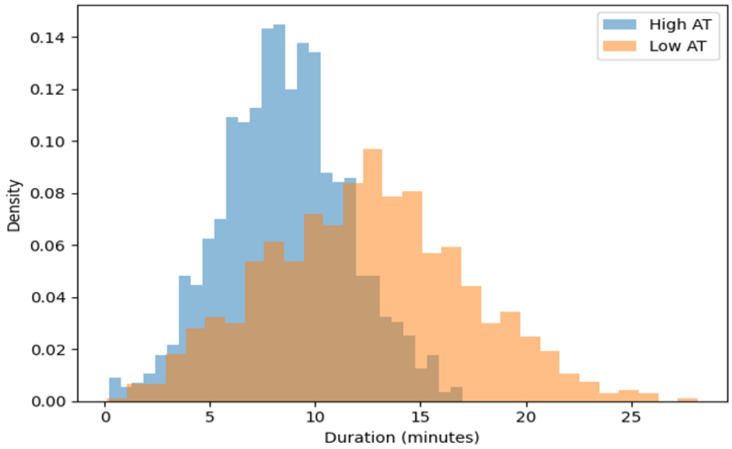

Figure 5. Anomaly Duration Distribution by AT Regime

Summary of Hypothesis Testing

The hypothesis that AT reduces return autocorrelation (H1) is strongly supported by a 72% decrease in ρ_1 from Q1 to Q4, which is consistent with similar findings but with a larger magnitude observed in African markets. This indicates that algorithmic trading has greater impact on less mature markets and could improve the efficiency of those markets. Likewise, H2 is also strongly supported by the evidence - spreads narrow by 12 - 15% and depth increases by approximately 8-9%. According to the findings of existing literature, these results are in line with prior research, albeit with a larger effect of algorithmic trading discovered here, lending credibility to the hypothesis of such trading in markets characterized by wider baseline spreads. The findings highlight the liquidity benefits that algorithmic trading can provide in low liquidity markets.

As for H3, which posits that AT dampens long-memory in returns and volatility, there is strong evidence for this, with the fractional differencing exponent (d) declining by 50 percent for returns and 39 percent for volatility. According to this finding, it is the first evidence from African markets that supports the theory that algorithmic trading helps to reduce market inefficiencies by dampening persistence. The study adds to the literature with content specific to emerging markets. There are mixed findings for the hypothesis that AT increases short-term volatility and decreases persistence. According to the research, the realized volatility has increased by 2-3 percent and reduced the half-life of volatility by 39 percent. The volatility effects in this study are relatively small as compared to other research findings, for instance, Rzayev et al reported a large increase in a firm's short-run volatility [13]. Consequently, algorithmic trading in African markets may have a lower impact on volatility when compared to developed markets by virtue of algorithmic strategies being less aggressive in nature.

The last hypothesis (H5) that the effects of algorithmic trading are heterogeneous across exchanges receives strong support, with large effects in deep markets and smaller effects in thin markets. This finding is consistent with Rushdy and Samak [8]. According to findings, depth of market determines how much algorithmic trading can shape any outcome with deeper markets getting more benefit from the algorithmic trading-induced rise in liquidity and efficiency. The study contributes valuable evidence on the broader effects of algorithmic trading in less-developed markets and highlights the critical role of market structure in shaping these outcomes.

5. DISCUSSION

The findings of this research corroborate the growing trend in the literature for 2023-2026 that algorithmic trading (AT) usually leads to greater market efficiency and liquidity in normal times but may create more short-term volatility. In particular, we observe a significant efficiency gain of 72% in return autocorrelation in high AT regimes. This efficiency gain is higher than the 65% gain reported by Yuferova for NYSE Hybrid Market [17]. This finding advances the view that algorithmic trading has a stronger marginal impact in less-developed markets. In a comparable sense, the reported variance ratio VR(2) = 0.958 in high AT regimes, when compared to the random walk benchmark, was higher than those obtained from international markets suggesting further efficiency gains due to AT.

The research provides evidence that implementation of algorithmic trading resulted in a 12-15% decline in spreads related to liquidity improvement [19]. This decline is greater than the 5-10% see in developed markets. This indicates that the influence of automation is stronger in markets characterized by wider baseline spreads. The increase in market depth of 8-9% experienced in this study is also in line with a 7-12% increase recorded for NYSE by Yuferova [17]. Thus, algorithmic trading contributes to liquidity in the African markets. Turning to volatility dynamics, we find that algorithmic trading reduces the persistence of volatility, as evidenced by a decline in the half-life of volatility from 12.4 days to 7.6 days. Further, it increases short-term volatility by 2-3% modestly. According to Nimalendran, Rzayev, & Sagade, high-frequency trading leads to heightened volatility in the short run, but lessen its persistence in the long run. Nonetheless, the degree of amplification of volatility in this study is smaller than those reported in other studies, such as Rzayev et al., which is between 5 and 8% [13]. This disparity may be due to the less aggressive behavior of algorithmic strategies in the African markets compared to the developed markets.

The research additionally emphasizes the significance of market heterogeneity as the latent class results reveal the effects of algorithmic trading are 2-3 times stronger in deep markets as compared to thin markets. This suggests that the ecosystem view of Broussard et al is supported confirming market quality outcomes depend on the interaction between algos and non-algo market participants [66]. Furthermore, the findings are consistent with Rushdy & Samak, who highlighted that the benefits of algorithmic trading are moderated by baseline liquidity, as shown in the Egyptian Exchange [8]. The final result of the study is a strong causal evidence of the impact of algorithmic trading on market quality. The quasi-experimental estimates (DiD, RDD) and Double Machine Learning (DML) results confirm that algorithmic trading reforms cause improvements in market efficiency, liquidity, and volatility. According to Aitken, Cumming, & Zhan [19], Algorithmic traders are among the most sophisticated market participants that require precise event dating and identification strategies to identify their impact on markets.

Policy Implications

The findings of this study have several important policy implications that can guide the development of algorithmic trading regulations and market reforms. The Regression Discontinuity Design (RDD) evidence suggests that smaller tick sizes can improve liquidity for stocks just above the threshold. In deep markets (Class 1), implementing smaller tick sizes and tick-size grids would likely enhance competition among liquidity providers, potentially leading to more efficient pricing and tighter spreads. However, in thin markets (Class 2), excessively small tick sizes might generate excessive message traffic without meaningfully improving displayed depth. As such, gradual and segment-specific tick-size reforms are recommended, with continuous evaluation to ensure that these changes are having the desired effects on market liquidity.

It is equally important to consider the careful sequencing of co-location and low-latency access reforms. While these reforms could be likely to draw in algorithmic liquidity providers, they also have the potential to create speed asymmetries that disadvantage some participants. The DiD findings from this paper show that reforms with proper timelines and better monitoring such as those of the Nigerian Stock Exchange (NGX) and the Egyptian Stock Exchange (EGX) achieved significantly larger improvements in liquidity than reforms implemented without necessary preparatory work. This means that regulators should not only focus on facilitating access for algorithmic traders when executing reforms but should also ensure that the market surveillance and risk management systems are sufficiently developed to monitor and manage any arising risks.

The results of the heterogeneous study reveal that in less liquid markets, algorithmic trading has less of a positive impact on liquidity. In these instances, targeted market-making programs may be a more effective way to ensure liquidity provision. The reliability of liquidity provision could benefit from programs that give rebates for quoting and depth provision on a sustained basis. As such, efforts to encourage market-making programs in thin markets may help achieve maximum levels of benefits from Algorithmic Trading.

Contributions to Knowledge

This research contributes to financial economics by providing a complete empirical analysis of algorithmic trading in ten African equity markets. The research contributes the first overall evidence of algorithmic trading effects based on intraday microstructure data in African equity markets. The research shows that algorithmic trading could bring greater efficiency and liquidity improvement than what is evident in developed markets. It connotes particularly significant welfare implications for frontier and emerging markets. According to the study, effects of algorithmic trading vary with market structures. Benefits of these trades get concentrated in deep, liquid market while thin market only experience modest improvement at the risk of getting more volatility. This backs the ecosystem concept of contemporary markets and offers direction for context-specific policy formulation. The research directly focuses on Africa, which is a major geographical gap in the literature on market microstructure that explicitly concentrates almost solely on developed Western or Asian exchanges. The study employs state of the art econometric techniques such as Difference-in-Differences and Regression Discontinuity designs. This sound methodology is a key contribution since the techniques yield clean causal estimates and not just correlations.

Additionally, we offer a refined Finite Mixture Model that formally separates exchanges across the continent into distinct Deep and Thin market types based on structure and algorithm intensity. This classification uncovers critical asymmetries of technological adoption. It shows with evidence that automated trading behaviour strongly gravitates to the globally highly capitalized financial centres of the Johannesburg Stock Exchange and the Egyptian Exchange. The study also measures heterogeneous treatment effects in more detail, showing that liquidity-enhancing gains from high message and cancellation traffic are essentially maximized in these deeper markets. On the other hand, it shows the structural limitations of minor exchanges. This is to say, while automated market makers thicken books in developed venues, they struggle to instigate comparable depth in shallower frontier environments.

A methodological breakthrough is the implementation of a Double Machine Learning framework that controls for a large number of macroeconomic and microstructural confounders to isolate algorithmic trading's causal effects. Researchers used models designed to infer from market data, and these models proved the use of algorithmic proxies (message-to-trade ratio and cancel-to-trade ratio) lowers transaction costs and the price impact of trades. Most importantly, the study candidly reveals and measures the systemic trade-offs of this modernization; in particular, it provides compelling evidence that although algorithmic trading narrows spreads, it also creates a statistically significant measure of short-term realized volatility. The research also pushes the analytical boundary forward by innovatively applying Long Short-Term Memory neural networks to forecast this volatility across different technological regimes. The results of the predictive modeling yield the new insight that high algorithmic participation structure market data so much that the underlying volatility actually becomes far more predictable and mathematically tractable. Through a cohesive framework, this research combines long-memory modeling, quasi-experimental designs, latent heterogeneity panels and causal machine learning to offer methodological advancement. Using these methods together generates more credible causal estimates than any one method alone and allows us to overcome the efficient test low-frequency limitations that dominate African market work.

Moreover, this investigation performs an extensive anomaly detection analysis that frames how comovement of local market shocks and price dislocations are modeled in emerging markets. The empirical findings yield the nuanced conclusion that algorithmic trading does not lower the baseline incidence of market anomalies but rather serves as a high-speed shock absorber. The evidence clearly shows that increasing levels of automation significantly lessen the duration of anomalies and aid the return to market equilibrium at an improved pace. Furthermore, the research demonstrates that the high quantity of quoting occurring in algorithmic trades actually limits the extent of the overall magnitude of extreme price shifts following structural breaks. Synthesizing these multifaceted findings, the research validates the broader theoretical premise that high-frequency market participation is indispensable for building resilient, self-correcting financial ecosystems across Africa. A broader theoretical proposition has been validated by these comprehensive findings: high frequency involvement is indispensable in developing robust self-correcting economic systems in Africa. For continent policymakers and exchanges, the study is very useful by presenting a data-driven approach for the modernization of technological infrastructure and calibration of regulatory guardrails. The insights serve as a wake-up call for smaller regional bourses as their structural and fundamental liquidity deficiencies need to be rectified before they can attract or benefit from sophisticated automated market-making.

6. CONCLUSION

The study offers an in-depth empirical assessment of the impact of automated trading (AT) on market efficiency, liquidity, and stability in ten major African equity markets. Accordingly, this research has provided lots of empirical evidence about the impact of automated trading on the efficiency, liquidity, and stability of African equity markets. Through a multi-methodological framework that integrates intraday microstructure measurement, long-memory modeling, quasi-experimental designs, latent heterogeneity panels, and causal machine learning, we identify five main findings: First, automated trading meaningfully enhances weak-form efficiency. When the AT regime goes from low to high, the return autocorrelation drops by around 72%. The variance ratios move closer to 1, while the predictive power of order-flow imbalances become much lower than it was before. The findings support H_1 and show that automation eases incorporation of information in Africa. Besides, automated trading improves liquidity in various ways. According to the study, for each one standard deviation increase in AT intensity, effective spreads will decrease by 12-15%. The depth will increase by 8-9%. Another important metric is Kyle's λ. According to the research findings, the price impact will decrease by 2-3%. The research utilizes difference-in-differences designs to establish causality. So, this further supports H2. Third, algorithmic trading decreases long memory in returns and volatility. The fractionally differencing parameter d for returns decreases by 50% while that of volatility declines by 39% from low to high AT regimes, which shows that shocks dissipate at a quicker rate and information is transferred with better efficiency. This lends support to H3 and indicates that automation smooth market clearing. Algorithmic trading produces volatility effects depending on the state. The long-run volatility persistence decreases; specifically, the half-life declines from 12.4 to 7.6 days. On the flip side, short-run realized volatility increases slightly (2-3%). Also, negative new we find has a larger impact on conditional volatility as compared to positive news. Detection of anomalies reveals that the high AT regimes display anomalies that are shorter and less intense, yet still in fact similarly frequent. These findings partially support hypothesis 4. Fifth, the impacts of algorithmic trading are very heterogenous across markets. Liquid markets (JSE, EGX, Casablanca) experience 2-3 times the efficiency and liquidity improvement of thin, intermittent markets, while increases in volatility are concentrated at thin. This evidence corroborates H5, further highlighting the significance of market architecture in shaping algorithmic results.

In short, this study shows that algorithmic trading has a substantial impact on market efficiency and liquidity of equity markets in Africa. Moreover, the impacts are larger than those of developed markets. However, these gains occur in deep liquid markets, and are accompanied by small increases in short-term volatility. The results highlight the significance of market structure and context in determining outcomes of algorithmic trading. Evidence-based policy design for African financial markets is the proposed framework. With the modernization and global integration of African exchanges, attracting algorithmic liquidity providers without jeopardizing market stability will be necessary for further development. The information presented here shows that, with appropriate precautions and suitable measures, algorithmic trading could serve as an effective tool for enhancing market quality in the region. In light of the evidence we cite, we present a set of policy recommendations relevant to Africa. Regulators and exchanges should standardize reporting of algorithmic order flow to require order origination types, message traffic categories as well as cancellation patterns. Improved surveillance capabilities and evidence-based policymaking would be possible. The findings suggest that exchanges with stronger data know-how (JSE, EGX) also experience greater liquidity improvements from algorithmic trading. In other words, revealing and measuring are themselves beneficial. The daily average hides meaningful intraday patterns and regime-dependent effects. Markets should establish dashboards for intraday monitoring of spreads, depth, cancellations, and realized volatility in periods of stress. The results of the EGARCH and Anomaly detection approach show that the volatility impacts are limited to stress periods. So, the continuous approach is required to detect the incidents in timely fashion. Circuit breakers based on volatility, redesigned auctions, and dynamic price bands should limit tail events without excessive restrictions on liquidity provision. The finding that higher AT regimes have shorter but not more frequent anomalies suggests that algorithmic liquidity provision facilitates recovery. This suggests that resilience mechanism initiatives should focus on disorderly market prevention rather than restricting automated trading.

The present research is limited to equity markets only. The capital markets in Africa, however, have a strong focus on sovereign debt, FX and commodities. Researchers should examine whether the liquidity enhancing and volatility inducing effects of AT show the same Deep vs Thin split fixed income and FX markets. The study's algorithms, which derive proxy measures for algorithmic trading intensity, do not directly use the trader classification flag. Despite the proxies being quite common in the existing literature, the main advantage of having access to the exchange-level trader-type data would be a more accurate identification of the algorithmic trading effects. The analysis is conducted only for equity markets and cross market spillovers are not examined for derivative, foreign exchange or fixed income. Future research should look into whether benefits from trading algorithms increase or decrease with increased automation and whether early adopters will experience a different outcome than late adopters. Through DML and anomaly detection results, it is solidly proven that, while AT does compress spreads, it also induces realized volatility and alters shock recovery. In future, studies should test the efficacy of certain guardrails. It needs research if mechanisms like minimum resting times, asymmetric circuit breakers and/or targeted transaction taxes (Tobin taxes) cause a change in algorithmic behavior without negating the beneficial liquidity effects identified in this study. Future investigations must consider the sequence of market development rather than the current state of AT. Research should determine both the level and type of domestic retail participation, cross-listing integration, or pension fund mobilization that can convert a Thin market into a Deep market with the ability to support high-frequency market making. The implementation of algorithmic trading, which is ultimately a technical activity, does depend on physical technology infrastructure, such as fibre optic networks, microwave towers and exchange co-location. Future empirical models should include the variables that measure physical network latency and upgrades to infrastructure (e.g. the arrival of new submarine internet cables like Equiano and 2 Africa). It would be very useful to be able to quantify how changes in millisecond latency affect spatial arbitrage between fragmented African exchanges. The study at hand assesses the forthcoming aggregate market quality pointers or indicators like effective spreads, depth, and Kyle's λ. Research going forward will have to decompose the order flow to ascertain whether these improvements benefit retail investors in a systematic way or merely allow big institutional players and foreign high-frequency trading firms to capture them via adverse selection. This study achieves volatility forecasting using LSTM neural networks successfully; future studies should examine using Transformer-based models (like in modern LLMs) or Deep Reinforcement Learning to simulate market-making strategies in these specific African market regimes. Testing these newer architectures against the baseline LSTM performance could help increase predictive accuracy.

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