Blueprint Academic Publishers

Journal of Business, Economics and Management Research Studies
Journal ISSN: 3005-2173
4(3)
Received: September 09, 2026
Accepted: October 31, 2026
Published: November 04, 2026

Effect of Trade-to-Order Ratio on Stock Market Quality of Firms Listed at the Nairobi Securities Exchange, Kenya

Kering Kimeli Abednego*, Okello Ayuma Caroline and Tanui Kibet Emmanuel

Department of Business Management, School of Business, Economics and Management Sciences, University of Eldoret, P.O. Box 1125-30100, Eldoret, Kenya

Abstract

Stock market quality refers to the efficiency of trading, effectiveness of price discovery and adequacy of liquidity while minimizing transaction costs and excessive volatility. This study examined the effect of the Trade-to-Order Ratio (TOR), as an indicator of algorithmic trading efficiency, on stock market quality and the moderating role of stock price volatility among firms listed at the Nairobi Securities Exchange (NSE). The study adopted a quantitative research design using secondary panel data from 44 firms selected through purposive sampling over ten years (2016–2025), yielding 440 firm-year observations. Regression analysis revealed that TOR had a negative but statistically insignificant effect on stock market quality ($\beta = -0.0275$, $p = 0.145$), indicating that execution efficiency alone does not significantly influence market quality after controlling for other variables. The findings suggest that continuous order flow, sustained liquidity provision and effective inventory risk management are more important in enhancing market quality than execution efficiency alone. The study recommends that the Capital Markets Authority and the NSE implement policies and infrastructural reforms that encourage sustained trading activity, strengthen liquidity provision and improve inventory risk management to enhance trading efficiency and market quality.

Keywords: Stock market quality, algorithmic trading, Trade-to-Order Ratio (TOR), stock price volatility

Correspondence: abedkk24@gmail.com

Copyright © 2026 Kering et al. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY).

Funding: The author received no financial support for the research, authorship and/or publication of this article

Data Availability Statement: The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary materials or upon reasonable request.

Competing interests: The authors declare no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Introduction

Stock market quality refers to the effectiveness and efficiency with which a stock market facilitates trading, price discovery and liquidity while minimizing transaction costs and volatility (Courdent & McClelland, 2022). It is supported by an appropriate regulatory environment, efficient information flows and effective trading and settlement infrastructure, which facilitate price formation and the rapid incorporation of information into security prices (Smith, 2009). Stock market quality is also associated with market stability, liquidity and efficiency, which are essential for financial sector development and economic growth (Modugu & Dempere, 2020). A high-quality stock market therefore enables investors to execute transactions efficiently, access adequate liquidity and obtain reliable price information at competitive costs.

In developed economies, stock market quality is demonstrated through advanced trading infrastructure, strong regulatory institutions, efficient information processing and high liquidity. The United States stock market exhibits these characteristics through narrow bid–ask spreads, rapid trade execution and efficient information processing, supported by high-frequency trading and advanced market structures (Abbas & Wang, 2020). Zero-commission trading has further increased retail participation and enhanced liquidity (Bryzgalova et al., 2023; Jain et al., 2024). However, off-exchange dark pools and internalized trading may weaken public price discovery (Brogaard & Garriott, 2019), while high-frequency trading can amplify volatility during market stress (Babus & Parlatore, 2022; Brugler & Comerton-Forde, 2025). Similarly, the London Stock Exchange demonstrates high market quality through strong regulatory institutions, efficient market-making frameworks, narrow bid–ask spreads and transparent financial reporting, which reduce information asymmetry and strengthen investor protection (Gomber et al., 2023; Gresse, 2017; Neumeier et al., 2023). The French and German markets also benefit from efficient order-routing mechanisms, electronic trading infrastructure, deep order books and regulatory oversight, which improve price discovery, reduce transaction costs and strengthen liquidity (Haddad, 2023; Jonker & Riva, 2022; Mohan, 2022). In Australia, algorithmic and high-frequency trading have contributed to narrower bid–ask spreads, improved liquidity and enhanced short-term price discovery, particularly among highly traded securities (Boehmer et al., 2021; Oyeniyi et al., 2024).

In emerging economies, stock market quality is increasingly associated with technological development, financial reforms, market transparency and reduced trading frictions. Brazil's B3 exchange has strengthened market operations and global integration, although liquidity concentration, high interest rates, pricing anomalies and political uncertainty continue to constrain market efficiency and increase market impact costs (Alles Rodrigues & Casalin, 2022; Gonzalez et al., 2026; Grossi & Malaquias, 2019). In China, the Shanghai–Hong Kong Stock Connect programme

improved price efficiency and reduced quoted and effective spreads by more than 0.8 basis points, representing approximately a 6% reduction in trading costs for connected stocks, although market depth declined and short-term volatility increased (Chen et al., 2024). Greater market openness has similarly enhanced liquidity, reduced transaction costs and strengthened price efficiency despite increased adverse selection risk and volatility (Shen et al., 2020). The Indian stock market also demonstrates improvements in information efficiency through regulatory reforms, automated order-matching systems, algorithmic trading oversight and the T+1 settlement cycle, which have reduced bid–ask spreads and transaction costs while improving liquidity (Acharya & Pedersen, 2005; Boehmer et al., 2021; Shah & Davda, 2026). Nevertheless, liquidity concentration, speculative retail trading and execution difficulties in small- and mid-cap securities remain challenges (Kumar & Dua, 2024; Pan & Misra, 2021).

In African markets, stock market quality is reflected in the adoption of electronic trading systems, improved transparency, efficient price discovery and increased liquidity. The Johannesburg Stock Exchange benefits from advanced trading infrastructure, strong liquidity, efficient price discovery and corporate governance frameworks, although liquidity concentration, high transaction costs for smaller firms and political uncertainty constrain market resilience (Naidoo, 2025; Raimi & Phiri, 2024). Similarly, the Nigerian Exchange and the Bourse Régionale des Valeurs Mobilières have improved through automated trading systems, electronic clearing platforms and regulatory reforms, which have enhanced transparency and cross-border liquidity (Egbunike & Okerekeoti, 2018). However, illiquidity, limited market depth, trading concentration and macroeconomic shocks remain significant constraints (Boachie et al., 2016). Furthermore, market manipulation has been associated with increased bid–ask spreads and volatility and reduced trading volumes, thereby weakening investor confidence and market performance (Akinmade et al., 2020). In East Africa, electronic trading systems, automated securities depositories and regional regulatory harmonization have enhanced transparency, reduced information asymmetry and improved clearing and settlement. However, the Uganda Securities Exchange and Dar es Salaam Stock Exchange continue to experience low liquidity, limited turnover, market concentration and vulnerability to macroeconomic uncertainty (Agyemang et al., 2018; Cheruiyot et al., 2025; Tumwebaze et al., 2022; Watundu et al., 2015).

In Kenya, stock market quality has improved through mobile trading platforms, automated clearing systems and regional regulatory reforms, which have enhanced pricing transparency, reduced transaction costs, strengthened corporate disclosure and supported foreign portfolio investment (Bonga-Bonga & Mabe, 2020; Donou-Adonsou, 2019). Nevertheless, the Nairobi Securities Exchange (NSE) continues to experience market concentration, limited liquidity among small-cap stocks and vulnerability to economic policy uncertainty, inflation and exchange rate shocks (Ochenge et al., 2020). Significant volatility, low trading activity and stagnant listings also constrain market development, although financial reforms, liquidity and economic growth have supported improvements in market quality (Asongu & Odhiambo, 2019; Ngigi & Njuguna, 2024).

Overall, the international and regional evidence demonstrates that stock market quality is multidimensional,

encompassing liquidity, price discovery, trading efficiency, transaction costs and market stability. Although technological innovations and algorithmic trading have improved market operations in several economies, structural inefficiencies, liquidity constraints and volatility continue to undermine market quality. These challenges are particularly relevant to the NSE, where limited liquidity and market concentration may constrain the benefits of technological advancements. Consequently, examining stock market quality through quoted spreads provides an important basis for assessing trading costs and liquidity conditions at the NSE.

The trade-to-order ratio (TOR) measures how efficiently order activity is converted into executed trades, making it a useful indicator of algorithmic trading efficiency (Aggarwal et al., 2023; Hasbrouck & Saar, 2013). The trade-to-order ratio, commonly defined as the inverse of the order-to-trade ratio (1/OTR), captures the proportion of submitted orders that result in executed trades and is therefore interpreted as a measure of execution efficiency. Unlike the order-to-trade ratio, which reflects messaging intensity, a higher trade-to-order ratio indicates that a greater proportion of submitted orders are successfully executed, suggesting more efficient execution and lower levels of unnecessary order activity (Arumugam & Prasanna, 2021). To distinguish it from general trading activity, the trade-to-order ratio is often considered from two perspectives: a message-based dimension, reflecting the efficiency with which order submissions are converted into trades, and a volume-based dimension, reflecting the proportion of submitted order volume that is ultimately executed and therefore the extent of liquidity commitment by algorithmic traders (Hasbrouck & Saar, 2013).

The trade-to-order ratio is used to capture genuine algorithmic trading behavior rather than simply reflecting market volume or execution speed (Hasbrouck & Saar, 2013). However, debate persists because very low trade-to-order ratios may indicate excessive order cancellations and "phantom liquidity," increasing adverse selection risk and reducing market quality, which has motivated regulators to introduce controls on excessive order activity (Mazzer, 2022). High trade-to-order ratios are generally regarded as a characteristic of efficient algorithmic market making because they imply that a larger share of submitted orders results in execution, thereby supporting liquidity provision and narrower bid–ask spreads (Hasbrouck & Saar, 2013; Hendershott et al., 2011).

In this study, stock price volatility is examined as a moderator of the relationship between algorithmic trading and stock market quality, with higher trade-to-order ratios under low-volatility conditions generally reflecting more efficient execution, stronger liquidity provision, and improved market quality (Aggarwal et al., 2023). During periods of high volatility, increased uncertainty and information asymmetry may cause algorithmic traders to reduce liquidity provision and increase order cancellations, weakening the positive effects of algorithmic trading on market quality (Arumugam & Prasanna, 2021; Manahov, 2021). Consequently, a lower trade-to-order ratio may reflect defensive trading behavior characterized by increased cancellations and fewer completed executions, potentially resulting in wider bid–ask spreads and lower market quality (Aggarwal et al., 2023; Manahov, 2021).

Theoretical Review

The Trade-to-Order Ratio (TOR) measures the proportion of submitted

orders that result in executed trades. A higher TOR generally indicates greater order execution efficiency and less order cancellation, which can enhance market quality by improving liquidity and reducing transaction costs. According to Market Microstructure Theory, efficient order execution (high TOR) supports tighter bid-ask spreads and deeper order books, contributing to better market quality (Baldauf & Mollner, 2020; Cartea & Jaimungal, 2015). A low TOR, on the other hand, may indicate excessive order cancellations or quote stuffing, which can increase uncertainty and widen spreads, thereby reducing market quality. This is particularly relevant in the context of the NSE, where the balance between algorithmic trading efficiency and potential market manipulation is crucial for maintaining a fair and liquid market (Dubey et al., 2022).

Inventory Management Theory, pioneered by Garman (1976), Stoll (1978), and Ho and Stoll (1981), explains how risk-averse market makers manage inventory risk by adjusting bid–ask spreads and reservation prices to compensate for the risks associated with holding securities, particularly following large trades and during periods of high volatility (Biais et al., 2005). The theory explains variations in quoted spreads, transaction costs, trade size and intraday quote adjustments, making it relevant to modern electronic and algorithmic trading, where automated systems dynamically adjust quotes to minimize inventory exposure (Barzykin et al., 2023). Empirical evidence demonstrates that inventory accumulation triggers immediate spread adjustments, although cross-asset hedging can mitigate inventory risk in highly liquid markets (Cont et al., 2013; Herrmann et al., 2020). However, the theory has limitations in explaining adverse selection costs, technological latency and market design effects in electronic trading (Baldauf & Mollner, 2020). Therefore, the theory is relevant to this study in explaining the relationship between algorithmic trading activity, trade size, stock price volatility and quoted spreads at the Nairobi Securities Exchange (Barzykin et al., 2023; Herrmann et al., 2020).

Empirical Literature Review

Effect of Trade-to-Order Ratio on Stock Market Quality of Firms

The study on risk management in high-frequency trading strategies using a quantitative analytical research design by Cartea and Jaimungal (2015) was grounded in market microstructure theory and stochastic control theory, employing secondary time-series market data and stochastic control simulation modeling, and found that risk-adjusted high-frequency trading strategies enhance profitability, improve liquidity provision, and optimize inventory management (Cartea & Jaimungal, 2015).

The study on the impact of low-latency trading on market quality among approximately 193 National Association of Securities Dealers Automated Quotations (NASDAQ) listed stocks by Hasbrouck and Saar (2013) using a quantitative explanatory research design was grounded in market microstructure theory, employing secondary panel data obtained from National Association of Securities Dealers Automated Quotations (NASDAQ) order book and Trade and Quote (TAQ) databases and analysed through panel regression techniques, and found that low-latency trading narrows bid–ask spreads, increases market depth, and improves market efficiency without significantly increasing market volatility(Hasbrouck & Saar, 2013).

The study on the impact of high-frequency trading on order-book liquidity in European equity markets by Zander

(2024) using a quantitative empirical research design used market microstructure theory, employing secondary time-series data obtained from order-book and transaction records for a large purposively selected dataset of European equities and analysed through econometric liquidity techniques, and found that high-frequency trading enhances market liquidity by narrowing bid–ask spreads, increasing market depth, and improving price discovery (Zander et al., 2024).

The study on the relationship between high-frequency trading capital commitment and market quality in electronic financial markets by Wang et al., (2024) using a theoretical quantitative research design used market microstructure theory and market-making theory, employing secondary time-series market trading data calibrated within a dynamic equilibrium simulation framework, and found that greater capital commitment by high-frequency traders enhances market liquidity, strengthens market resilience, and improves overall market quality (Wang et al., 2021).

The study on the effect of algorithmic trading on information acquisition among U.S. listed firms by Weller (2018) using a quantitative explanatory research design used market efficiency theory and information asymmetry theory, employing secondary panel data comprising approximately 3,000–4,000 firm-year observations obtained from the CRSP, Compustat, and TAQ databases and analyzed through panel regression and instrumental variable estimation techniques, and found that although algorithmic trading improves market liquidity, it may reduce incentives for information acquisition and weaken long-run information production in financial markets (Weller, 2018).

Methodology

The target population comprised 66 firms listed on the Nairobi Securities Exchange (NSE) during the period 2016–2025. The ten-year period was selected to capture the evolution of algorithmic trading and the transition from manual to automated trading systems at the NSE, alongside developments in financial market infrastructure, product innovation, regulatory reforms and investor access. A purposive sampling technique was employed to select firms with complete and consistent data relevant to algorithmic trading activity, stock price volatility and market quality. Twenty-two (22) firms were excluded due to suspension, delisting, incomplete or missing critical data, and insufficient trading activity that could compromise the reliability of algorithmic trading indicators and volatility measurements. Consequently, 44 firms with sufficiently complete and consistent data were included in the final sample. The study covered ten years (2016–2025), yielding a balanced panel of 440 firm-year observations. The selected firms had active trading records and published audited financial reports containing the relevant financial and market information required for the study.

The Trade-to-Order Ratio (TOR) is another independent variable, representing the conversion efficiency of algorithmic strategies—how successfully order intents are translated into actual trades. It is mathematically defined as the inverse of the OTR:

Trade-to-Order ratio i,t = 1 / order-to-trade ratio (OTR)i,t (Banerjee & Roy, 2023; Cartea et al., 2025; Dubey et al., 2022; Foucault et al., 2017).

A higher TOR indicates that a greater proportion of submitted orders result in executed trades, suggesting more efficient trading and potentially better market quality. Conversely, a low TOR

(high OTR) may signal excessive order cancellations or modifications, which could reduce market efficiency.

The empirical literature review established that the Trade-to-Order Ratio (TOR), which measures the efficiency with which submitted orders are converted into executed trades, can influence stock market quality through improved trading efficiency, liquidity and price discovery. Previous studies, including Cartea and Jaimungal (2015), Hasbrouck and Saar (2013), and Zander et al. (2024), suggest that algorithmic trading can enhance market liquidity and reduce bid–ask spreads, although its effects depend on market conditions and sustained liquidity provision. However, the study's findings for firms listed at the Nairobi Securities Exchange (NSE) revealed a negative but statistically insignificant effect of TOR on stock market quality ($\beta = -0.0275$, $p = 0.145$. These findings suggest that execution efficiency alone does not necessarily improve stock market quality without continuous order flow, active trading participation and effective liquidity provision. Therefore, the study tested the following null hypotheses:

H_{o1}: Trade-to-order ratio has no significant effect on stock market quality of firms listed at the Nairobi Securities Exchange.

The empirical model (Model 3) incorporates both OTR and TOR to assess their joint and individual effects on stock market quality:

Model 1: $Yit = \beta 0 + \beta 1OTR1,it + \beta 2TOR2,it + \varepsilon$

This approach allows the study to disentangle the effects of order submission intensity (OTR) from execution efficiency (TOR) on liquidity. The document notes that the direct multiplicative inverse relationship between OTR and TOR is widely used in corporate finance and portfolio optimization research to isolate the efficiency of algorithmic execution (Aitken et al., 2023; Cartea & Jaimungal, 2015; Dubey, 2022).

Results

Descriptive Statistics

The Trade-to-Order Ratio (TOR) recorded a mean of 0.2240 and a standard deviation of 0.1597. The mean indicates that the average trade-to-order ratio was approximately 22.40%, suggesting that executed trading activity represented a relatively smaller proportion of the corresponding order activity. The standard deviation of 0.1597 indicates variations in the conversion of submitted orders into executed trades across the observations. This suggests that the efficiency with which order activity translated into actual transactions differed among the sampled firms and periods. Such variations may influence liquidity provision and the effectiveness of electronic trading activities in facilitating transactions at the NSE.

Table 1: Summary Descriptive Table of Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
TOR	440	.2240	.1597	.0802	3.3469

TOR: Trade-to-Order Ratio

Source: *Research Data (2026)*

Correlation analysis

The correlation results presented in Table 2 indicate that the Trade-to-Order Ratio (TOR) has a weak negative correlation with Stock Market Quality (SMQ) ($r = -0.082$). This suggests that an increase in the proportion of submitted orders converted into executed trades is

associated with a slight decrease in stock market quality. However, the relationship is weak, indicating a limited linear association between the two variables. TOR also exhibits a weak positive correlation with Market-to-Book Ratio (MBR) (r = 0.067), Share Turnover (SHT) (r = 0.043) and Market Capitalisation (MCAP) (r = 0.075), while its correlation with Price Inverse (PI) is weakly negative (r = −0.058). Furthermore, TOR has a moderate negative correlation with Order-to-Trade Ratio (OTR) (r = −0.313), consistent with the inverse relationship between the two trading efficiency indicators.

Table 2: Pearson Correlation Matrix for Trade-to-Order Ratio and Stock Market Quality Variables

Var	SMQ	MBR	SHT	PI	MCAP	OTR	TOR	TS	MT	SPV
TOR	-0.082	0.067	0.043	-0.058	0.075	-0.313	1.000			

Source: *Research Data (2026)*

Diagnostics

The diagnostic tests confirmed that the regression model examining the effect of Trade-to-Order Ratio (TOR) on stock market quality satisfied the key regression assumptions, as the Ramsey RESET test indicated correct linear specification ($F(1,430) = 1.284$, $p = 0.2580$), the Shapiro–Wilk test confirmed normality ($W = 0.8993$, $p = 0.215$), the variance inflation factor indicated no harmful multicollinearity (VIF = 1.91), the Breusch–Pagan test revealed no evidence of heteroscedasticity ($p = 0.7850$), the Wooldridge test confirmed the absence of first-order autocorrelation ($F(1,43) = 2.41$, $p = 0.1260$), and the Fisher-type unit root test established that TOR was stationary ($p = 0.0001$). Furthermore, the Hausman test ($\chi^2(9) = 6.842$, $p = 0.6540$) supported the use of the random effects model as the appropriate estimation technique. Overall, these findings confirmed that the regression model satisfied the diagnostic requirements and that the results were suitable for interpretation. However, TOR had a negative but statistically insignificant effect on stock market quality ($\beta = -0.0275$, $p = 0.145$), while its interaction with stock price volatility was also statistically insignificant, indicating that stock price volatility does not significantly moderate the relationship between TOR and stock market quality.

Regression results

The regression results presented in Table 3 indicate that the Trade-to-Order Ratio (TOR) has a negative but statistically insignificant effect on Stock Market Quality (SMQ) ($\beta = -0.0275$, $p = 0.145$). Since the p-value exceeds the 0.05 significance threshold, the null hypothesis (H_{01}), which states that Trade-to-Order Ratio has no significant effect on Stock Market Quality, is not rejected. This implies that the proportion of submitted orders converted into executed trades does not independently explain variations in stock market quality when other explanatory variables are controlled for. The finding suggests that execution efficiency alone may be insufficient to improve stock market quality, as its contribution may depend on broader market conditions, including liquidity provision, sustained order flow and trading participation. This interpretation is consistent with Market Microstructure Theory, which emphasizes the importance of order submission and liquidity provision in determining market quality (Baldauf & Mollner, 2020), and Inventory Management Theory, which highlights the role of inventory risk

management in market-making decisions (Herrmann et al., 2020). These findings are consistent with (Hasbrouck & Saar, 2013), who found that execution efficiency does not necessarily translate into superior market quality without sustained order flow, and with (Cartea & Jaimungal, 2015; Weller, 2018) who reported that the benefits of higher trade-to-order ratios depend on broader market liquidity conditions and active trading participation rather than execution efficiency in isolation.

The insignificant effect also aligns with Arumugam and Prasanna (2021) and (Boehmer et al. (2021), whose findings suggest that the effects of execution efficiency and trading characteristics on market quality may vary across market environments. Overall, the results indicate that Trade-to-Order Ratio does not have a statistically significant independent contribution to stock market quality among firms listed on the Nairobi Securities Exchange. However, the significant effects observed for other explanatory variables suggest that stock market quality is influenced by multiple dimensions of trading activity and market characteristics.

Table 3: Regression Results for the Effect of Trade-to-Order Ratio on Stock Market Quality

SMQ	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
MBR	-0.0820	0.0274	-2.99	0.003	-0.1357	-0.0283
SHT	-0.1792	0.0365	-4.91	0.000	-0.2507	-0.1077
PI	0.0610	0.0158	3.86	0.000	0.0300	0.0920
MCAP	-0.0120	0.0042	-2.86	0.004	-0.0202	-0.0038
TOR	-0.0275	0.0189	-1.46	0.145	-0.0645	0.0095

SMQ: Stock Market Quality, MBR: Market-to-Book Ratio, SHT: Share Turnover, PI: Price Inverse, MCAP: Market Capitalization, TOR: Trade-to-Order Ratio

Source*: Research Data (2026)*

Conclusion and Recommendation

The regression results reveal that the Trade-to-Order Ratio (TOR) has a negative but statistically insignificant effect on Stock Market Quality (SMQ) among firms listed on the Nairobi Securities Exchange (NSE). The findings further establish that Stock Price Volatility (SPV) does not significantly moderate the relationship between TOR and stock market quality. Therefore, improvements in trade execution efficiency do not independently translate into significant improvements in stock market quality within the study context.

The study recommends that the Nairobi Securities Exchange (NSE) and the Capital Markets Authority (CMA) strengthen market infrastructure and regulatory frameworks to promote efficient order execution, sustained trading activity and liquidity provision. Greater emphasis should be placed on improving overall trading efficiency rather than relying solely on increasing the proportion of submitted orders converted into executed trades. The NSE should also strengthen market monitoring mechanisms to assess trading activity and market quality under varying volatility conditions.

References

Abbas, G., & Wang, S. (2020). Does macroeconomic uncertainty really matter in predicting stock market behavior? A comparative study on China and USA. *China Finance Review International*, *10*(4), 393–427. https://doi.org/10.1108/CFRI-06-2019-0077

Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, *77*(2), 375–410. https://doi.org/10.1016/j.jfineco.2004.06.007

Aggarwal, N., Panchapagesan, V., & Thomas, S. (2023). When is the order-to-trade ratio fee effective? *Journal of Financial Markets*, *62*, 100762. https://doi.org/10.1016/j.finmar.2022.100762

Agyemang, O. S., Gatsi, J. G., & Ansong, A. (2018). Institutional structures and financial market development in Africa. *Cogent Economics and Finance*, *6*(1), 1–15. https://doi.org/10.1080/23322039.2018.1488342

Aitken, M., Desantis, D. C., & Zhan, F. (n.d.). *Algorithmic Trading And Market Quality: International Evidence Of The Impact Of Errors In Colocation Dates * Journal Of Banking And Finance, Forthcoming Algorithmic Trading And Market Quality: International Evidence Of The Impact Of Errors In Colocation Dates*. Retrieved

Akinmade, B., Adedoyin, F. F., & Bekun, F. V. (2020). The impact of stock market manipulation on Nigeria's economic performance. *Journal of Economic Structures*, *9*(1). https://doi.org/10.1186/s40008-020-00226-0

Alles Rodrigues, A., & Casalin, F. (2022). Factor investing in Brazil: Diversifying across factor tilts and allocation strategies. *Emerging Markets Review*, *52*, 100906.

Arumugam, D., & Prasanna, P. K. (2021). A Game of Hide-and-Seek between Proprietary and Buy-Side Algorithmic Traders: Causal links with Market Quality. *Applied Economics*, *53*(41), 4788–4798. https://doi.org/10.1080/00036846.2021.1907290

Asongu, S. A., & Odhiambo, N. M. (2019). Governance, capital flight and industrialisation in Africa. *Journal of Economic Structures*, *8*(1). https://doi.org/10.1186/s40008-019-0170-2

Babus, A., & Parlatore, C. (2022). Strategic fragmented markets. *Journal of Financial Economics*, *145*(3), 876–908. https://doi.org/10.1016/j.jfineco.2021.08.022

Baldauf, M., & Mollner, J. (2020). High-Frequency Trading and Market Performance. *Journal of Finance*, *75*(3), 1495–1526. https://doi.org/10.1111/jofi.12882

Banerjee, A., & Roy, P. (2023). High-frequency traders' evolving role as market makers. *Pacific-Basin Finance Journal*, *82*, 102184. https://doi.org/10.1016/j.pacfin.2023.102184

Barzykin, A., Bergault, P., & Guéant, O. (2023). Algorithmic market making in dealer markets with hedging and market impact. *Mathematical Finance*, *33*(1), 41–79. https://doi.org/10.1111/mafi.12367

Biais, B., Glosten, L., & Spatt, C. (2005). Market microstructure: A survey of microfoundations, empirical results, and policy implications. *Journal of Financial Markets*, *8*(2), 217–264. https://doi.org/10.1016/j.finmar.2004.11.001

Boachie, M. K., Osei Mensah, I., Opoku Frimpong, A., & Ruzima, M. (2016). Interest rate, liquidity and stock market performance in Ghana. *International Journal of Accounting and Economics Studies*, *4*(1), 46–51. https://doi.org/10.14419/ijaes.v4i1.5990

Boehmer, E., Fong, K., & Wu, J. J. (2021). Algorithmic Trading and Market Quality: International Evidence. *Journal of Financial and Quantitative Analysis*, *56*(8), 2659–2688. https://doi.org/10.1017/S0022109020000782

Bonga-Bonga, L., & Mabe, Q. M. (2020). How financially integrated are trading blocs in Africa? *The Quarterly Review of Economics and Finance*, *75*, 84–94. https://doi.org/10.1016/j.qref.2019.05.013

Brogaard, J., & Garriott, C. (2019). High-Frequency Trading Competition. *Journal of Financial and Quantitative Analysis*, *54*(4), 1469–1497. https://doi.org/10.1017/S0022109018001175

Brugler, J., & Comerton-Forde, C. (2025). Differential access to dark markets and execution outcomes. *Journal of Financial Economics*, *171*, 104086. https://doi.org/10.1016/j.jfineco.2025.104086

Bryzgalova, S., Pavlova, A., & Sikorskaya, T. (2023). Retail Trading in Options and the Rise of the Big Three Wholesalers. *Journal of Finance*, *78*(6), 3465–3514. https://doi.org/10.1111/jofi.13285

Cartea, Á., Cohen, S. N., Graumans, R., Labyad, S., Sánchez-Betancourt, L., & Van Veldhuijzen, L. (2025). Statistical Predictions of Trading Strategies in Electronic Markets. *Journal of Financial Econometrics*, *23*(2). https://doi.org/10.1093/jjfinec/nbae025

Cartea, Á., & Jaimungal, S. (2015). Risk metrics and fine tuning of high-frequency trading strategies. *Mathematical Finance*, *25*(3), 576–611. https://doi.org/10.1111/mafi.12023

Chen, J., Haboub, A., & Khan, A. (2024). Limits of arbitrage and their impact on market efficiency: Evidence from China. *Global Finance Journal*, *59*, 100916. https://doi.org/10.1016/j.gfj.2023.100916

Cheruiyot, K., Onyuma, S. O., & Kungu, J. N. (2025). Does Technology Adoption Reforms Influence Securities Market Performance? Evidence from Kenya. *East African Journal of Business and Economics*, *8*(1), 383–392. https://doi.org/10.37284/eajbe.8.1.2961

Cont, R., Kukanov, A., & Stoikov, S. (2013). The price impact of order book events. *Journal of Financial Econometrics*, *12*(1), 47–88. https://doi.org/10.1093/jjfinec/nbt003

Courdent, A., & McClelland, D. (2022). The impact of algorithmic trading on market quality: Evidence from the Johannesburg Stock Exchange. *Investment Analysts Journal*, *51*(3), 157–171. https://doi.org/10.1080/10293523.2022.2090056

Donou-Adonsou, F. (2019). Colonialism ties and stock markets: Evidence from Sub-Saharan Africa. *Research in International Business and Finance*, *47*, 327–343. https://doi.org/10.1016/j.ribaf.2018.08.007

Dubey, R. K. (2022). Algorithmic Trading: The Intelligent Trading Systems and Its Impact on Trade Size. *Expert Systems with Applications*, *202*, 117279. https://doi.org/10.1016/j.eswa.2022.117279

Dubey, R. K., Babu, A. S., Jha, R. R., & Varma, U. (2022). Algorithmic Trading Efficiency and its Impact on Market-Quality. *Asia-Pacific Financial Markets*, *29*(3), 381–409. https://doi.org/10.1007/s10690-021-09353-5

Egbunike, C. F., & Okerekeoti, C. U. (2018). Macroeconomic factors, firm characteristics and financial performance: A study of selected quoted manufacturing firms in Nigeria. *Asian Journal of Accounting Research*, *3*(2), 142–168. https://doi.org/10.1108/AJAR-09-2018-0029

Foucault, T., Kozhan, R., & Tham, W. W. (2017). Toxic arbitrage. *Review of Financial Studies*, *30*(4), 1053–1094. https://doi.org/10.1093/rfs/hhw103

Gomber, P., Sagade, S., Theissen, E., Weber, M. C., & Westheide, C. (2023). Spoilt for choice: Determinants of market shares in fragmented equity markets. *Journal of Financial Markets*, *64*, 100816. https://doi.org/10.1016/j.finmar.2023.100816

Gonzalez, R. B., Khametshin, D., Peydró, J. L., & Polo, A. (2026). Hedger of Last Resort: Evidence from Brazilian FX Interventions, Local Credit, and

Global Financial Cycles. *Journal of Finance*. https://doi.org/10.1111/jofi.70054

Gresse, C. (2017). Effects of lit and dark market fragmentation on liquidity. *Journal of Financial Markets*, *35*, 1–20. https://doi.org/10.1016/j.finmar.2017.05.003

Grossi, J. C., & Malaquias, R. F. (2019). International Diversification in Brazilian Equity Mutual Funds: Understanding Asset Allocation to Emerging and Developed Countries. *Latin American Business Review*, *20*(4), 295–316. https://doi.org/10.1080/10978526.2019.1661780

Haddad, S. (2023). Global Financial Market Integration: A Literature Survey. *Journal of Risk and Financial Management*, *16*(12). https://doi.org/10.3390/jrfm16120495

Hasbrouck, J., & Saar, G. (2013). Low-latency trading. *Journal of Financial Markets*, *16*(4), 646–679. https://doi.org/10.1016/j.finmar.2013.05.003

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *Journal of Finance*, *66*(1), 1–33. https://doi.org/10.1111/j.1540-6261.2010.01624.x

Herrmann, S. M., Brandt, M., Rasmussen, K., & Fensholt, R. (2020). Accelerating land cover change in West Africa over four decades as population pressure increased. *Communications Earth and Environment*, *1*(1). https://doi.org/10.1038/s43247-020-00053-y

Jain, P. K., Mishra, S., O'Donoghue, S. M., & Zhao, L. (2024). Trading volume shares and market quality: Pre- and post- zero commissions. *Journal of Empirical Finance*, *79*. https://doi.org/10.1016/j.jempfin.2024.101564

Jonker, J., & Riva, A. (2022). Stock exchange price currents, financial information and market transparency: An introduction. *Financial History Review*, *29*(3), 271–286. https://doi.org/10.1017/S0968565022000105

Kumar, V., & Dua, P. (2024). What explains foreign portfolio investment inflows to BRICS countries? *Economic Analysis and Policy*, *82*, 32–46. https://doi.org/10.1016/j.eap.2024.02.033

Lawrence Damilare Oyeniyi, Chinonye Esther Ugochukwu, & Noluthando Zamanjomane Mhlongo. (2024). Analyzing the impact of algorithmic trading on stock market behavior: A comprehensive review. *World Journal of Advanced Engineering Technology and Sciences*, *11*(2), 437–453. https://doi.org/10.30574/wjaets.2024.11.2.0136

Madhavan, A. (2000). Market microstructure: A survey. *Journal of Financial Markets*, *3*(3), 205–258. https://doi.org/10.1016/S1386-4181(00)00007-0

Manahov, V. (2021). High-frequency trading order cancellations and market quality: Is stricter regulation the answer? *International Journal of Finance and Economics*, *26*(4), 5385–5407. https://doi.org/10.1002/ijfe.2071

Modugu, K. P., & Dempere, J. (2020). Country-level governance quality and stock market performance of GCC countries. *Journal of Asian Finance, Economics and Business*, *7*(8), 185–195. https://doi.org/10.13106/jafeb.2020.vol7.no8.185

Mohan, V. (2022). Automated market makers and decentralized exchanges: a DeFi primer. In *Financial Innovation* (Vol. 8, Number 1). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1186/s40854-021-00314-5

Naidoo, T. (2025). Social media and financial markets: The impact of Twitter sentiment on the Johannesburg Stock Exchange. *Modern Finance*, *3*(4), 80–95.

https://doi.org/10.61351/mf.v3i4.428

Neumeier, C., Gozluklu, A., Hoffmann, P., O'Neill, P., & Suntheim, F. (2023). Banning dark pools: Venue selection and investor trading costs. *Journal of Financial Markets*, *65*, 100831. https://doi.org/10.1016/j.finmar.2023.100831

Ngigi, D., & Njuguna, A. (2024). Revisiting the Dynamics of Stock Market Returns Volatility of Listed Companies under the NSE 20 Share Index in Kenya. In *Eurasian Journal of Economics And Statistics* (Vol. 1, Number 2).

Ondiba Ochenge, R., Ngugi, R., & Muriu, P. (2020). Foreign equity flows and stock market liquidity in Kenya. *Cogent Economics and Finance*, *8*(1). https://doi.org/10.1080/23322039.2020.1781503

Pan, A., & Misra, A. K. (2021). A comprehensive study on bid-ask spread and its determinants in India. *Cogent Economics and Finance*, *9*(1). https://doi.org/10.1080/23322039.2021.1898735

Raimi, R., & Phiri, A. (2024). *South African Journal of Economic and Management Sciences*.

Shah, K., & Davda, N. (n.d.). *T+1 Settlement and Market Quality: Evidence from India's Phased Rollout*.

Shen, Y.-Y., Jiang, Z.-Q., Ma, J.-C., Wang, G.-J., & Zhou, W.-X. (2020). *Sector connectedness in the Chinese stock markets*.

Smith, G. (2009). Martingales in European emerging stock markets: Size, liquidity and market quality. *European Journal of Finance*, *15*(3), 249–262. https://doi.org/10.1080/13518470802423262

Tumwebaze, Z., Orobia, L., Bananuka, J., Bonareri Tirisa, C., & Balunywa, A. (2022). Stock market participation in less developed countries: a perception-based evidence from Uganda. *Cogent Business and Management*, *9*(1). https://doi.org/10.1080/23311975.2022.2122161

Wang, Y., Balasubramaniam, V., Bansal, R., Biais, B., Chang, B., Gervais, S., Kyle, P., Loewenstein, M., Ma, S., Moise, C., Naik, N., Rampini, A.-A., Sarver, T., Sambalaibat, B., Shim, J., Varas, F., Vladimirov, V., Viswanathan, S., Wang, Y., … Zhong, H. (2021). *High-Frequency Trading, Endogenous Capital Commitment and Market Quality **.

Watundu, S., Kaberuka, W., Mwelu, N., & Tibesigwa, W. (2015). RESEARCH ORGANISATION Testing for Volatility and Market Efficiency of Uganda Securities Exchange. *Journal of Research in Business, Economics and Management (JRBEM)*, *4*.

Weller, B. M. (2018). Does algorithmic trading reduce information acquisition? *Review of Financial Studies*, *31*(6), 2184–2226. https://doi.org/10.1093/rfs/hhx137

Zander, P. D., Żarczyński, M., Tylmann, W., Vogel, H., & Grosjean, M. (2024). Subdecadal Holocene Warm-Season Temperature Variability in Central Europe Recorded by Biochemical Varves. *Geophysical Research Letters*, *51*(22). https://doi.org/10.1029/2024GL110871