
**TESTING WEAK-FORM MARKET EFFICIENCY ON THE NAIROBI
SECURITIES EXCHANGE: A TIME-VARYING APPROACH**

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Article Received: 03 April 2026

Article Revised: 23 April 2026

Published on: 13 May 2026

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DOI: <https://doi-doi.org/101555/ijrpa.6647>

ABSTRACT

This study investigates weak-form market efficiency on the Nairobi Securities Exchange (NSE) using a time-varying framework over the period January 2010 to December 2023. Departing from conventional static tests, we employ the Generalized Spectral (GS) test of Escanciano and Velasco (2006), the Automatic Variance Ratio (AVR) test, and a rolling-window sub-sample methodology to track efficiency dynamics across distinct market regimes. Using daily closing prices of the NSE All-Share Index (NASI) and a cross-section of 25 actively traded equities, we document pronounced time-variation in efficiency: markets exhibit predictability during periods of macroeconomic stress (2011–2012, 2015–2016, and 2020 COVID-19 shock) but approximate random-walk behavior during relative tranquility. The demutualization of the NSE in 2014 and the introduction of mobile-based trading in 2017 coincide with measurable improvements in informational efficiency. Panel-data regressions further reveal that trading volume, foreign investor participation, and market capitalization are significant positive determinants of efficiency, while inflation volatility exerts a negative effect. Our findings carry implications for portfolio managers, policymakers, and the Capital Markets Authority (CMA) of Kenya regarding market microstructure reforms and investor education programmes’.

KEYWORDS: Efficient Market Hypothesis; Nairobi Securities Exchange; Random Walk; Variance Ratio Test; Rolling Window; Emerging Markets; Time-Varying Efficiency
JEL Classification: G14; G15; C12; C22; O16

1. INTRODUCTION

The Efficient Market Hypothesis (EMH), as formalized by Fama (1970), remains among the most debated propositions in financial economics. In its weak form, the EMH asserts that current asset prices fully reflect all historical price and volume information, rendering technical analysis incapable of generating sustained abnormal returns. For advanced financial markets such as the New York Stock Exchange or the London Stock Exchange, weak-form efficiency has found broad empirical support (Lo & Mackinlay, 1988; Campbell, Lo & MacKinlay, 1997). However, the evidence for emerging and frontier markets in Sub-Saharan Africa is far more equivocal, and the Nairobi Securities Exchange (NSE) has become an increasingly important empirical laboratory given its status as one of the most developed exchanges on the continent.

The NSE, established in 1954, currently hosts 64 listed companies across eleven sectors with a total market capitalization exceeding KES 2.1 trillion (approximately USD 14.2 billion) as of December 2023 (NSE, 2024). Despite several modernization milestones—electronic trading in 2006, the Central Depository System, demutualization in 2014, and the M-Akiba mobile bond in 2017—NSE equities remain characterized by thin trading, concentrated ownership, and periodic episodes of illiquidity, conditions generally inimical to efficiency (Mlambo & Biekpe, 2007; Ntim, Opong & Danbolt, 2007).

Prior studies on NSE efficiency have almost exclusively employed static tests—unit-root tests, autocorrelation-based runs tests, or fixed-sample variance ratio tests—yielding mixed conclusions (Dickinson & Muragu, 1994; Olweny & Kimani, 2011; Muthama & Mutothya, 2013; Nyamosi & Muragu, 2019). Critically, these static frameworks impose the implicit assumption that efficiency is constant through time, an assumption directly challenged by Lo's (2004) Adaptive Markets Hypothesis (AMH), which holds that market efficiency evolves in response to changing environments, competitive pressures, and regulatory developments.

This paper contributes to the literature in three principal ways. First, we apply a battery of time-varying efficiency tests using rolling sub-sample windows to document how efficiency on the NSE has evolved from 2010 to 2023. Second, we assess whether identifiable structural events—the 2011 inflationary crisis, the 2014 demutualization, the 2017 elections, and the 2020 COVID-19 pandemic—correspond to measurable regime shifts in efficiency. Third, we estimate panel determinants of efficiency to identify the microstructural and macroeconomic drivers of predictability. The remainder of this paper is organised as follows: Section 2 reviews the relevant literature; Section 3 describes the data; Section 4 outlines the

methodology; Section 5 presents empirical results; Section 6 discusses implications; and Section 7 concludes.

2. LITERATURE REVIEW

2.1 The Efficient Market Hypothesis and Its Extensions

Fama (1970) provided the seminal taxonomy of market efficiency, distinguishing between weak, semi-strong, and strong forms based on the information set presumed to be reflected in prices. The weak form—the focus of this study—has been tested predominantly through random-walk models and variance ratio tests (Lo & MacKinlay, 1988). However, Grossman and Stiglitz (1980) raised a fundamental paradox: if markets are perfectly efficient, no investor has an incentive to gather information, yet information acquisition is precisely what keeps markets efficient. This tension motivated subsequent frameworks recognizing efficiency as a spectrum rather than a binary state.

Lo's (2004, 2005) Adaptive Markets Hypothesis reconciles the EMH with evolutionary principles from biology and behavioral finance, positing that market efficiency is neither constant nor permanent. Instead, the degree of predictability in returns fluctuates with changing market conditions, the entry and exit of market participants, and institutional reforms. Empirical support for the AMH has been documented across a range of markets: Urquhart and Hudson (2013) for the United States, United Kingdom, and Japan; Noda (2016) for Japanese bond markets; and Gyamfi (2018) for African stock exchanges including the Johannesburg Stock Exchange (JSE) and the Ghana Stock Exchange (GSE).

2.2 Evidence from African Emerging Markets

Research on weak-form efficiency in African markets has proliferated since the mid-2000s, spurred by growing foreign investor interest and capital market development programs. Appiah-Kusi and Menyah (2003) examined eleven African markets using EGARCH models and found mixed evidence, with only some markets satisfying weak-form efficiency. Mlambo and Biekpe (2007) applied runs tests and autocorrelation tests to nine African markets, documenting pervasive thin-trading effects that bias toward rejection of the random walk.

For the NSE specifically, Dickinson and Muragu (1994) was among the earliest studies, finding evidence against weak-form efficiency for weekly returns. In contrast, Olweny and Kimani (2011) used unit-root and autocorrelation tests over 2001–2010 and could not reject the random walk hypothesis, suggesting improvement over time. Muthama and Mutohya (2013) applied variance ratio tests to daily NASI returns from 2008 to 2012, finding significant autocorrelation at short holding periods. More recently, Nyamosi and Muragu

(2019) used ARIMA-GARCH models and found evidence of return predictability associated with day-of-the-week effects, consistent with the absence of weak-form efficiency.

A consistent thread across these studies is their static nature. None investigates whether efficiency varies across the 2010–2023 period during which the NSE underwent substantial structural transformation. Our paper addresses this gap directly by adopting the time-varying methodology advocated by Kim, Shamsuddin and Lim (2011).

3. DATA

3.1 Sample and Sources

Our primary dataset consists of daily closing prices for the NSE All-Share Index (NASI) and 25 individual equities spanning January 4, 2010 to December 29, 2023, yielding a maximum of 3,521 trading-day observations per series. Individual stocks are selected on the basis of continuous listing throughout the sample period and an average daily turnover exceeding KES 500,000, ensuring adequate liquidity for reliable inference. The securities span seven sectors: Banking (8 stocks), Manufacturing & Allied (5), Safaricom & Telecoms (2), Energy & Petroleum (4), Commercial Services (3), Real Estate (2), and Agricultural (1).

Price data are sourced from the NSE Market Intelligence database, supplemented by Bloomberg for missing observations. Macroeconomic variables—inflation, exchange rates, interest rates—are obtained from the Central Bank of Kenya (CBK) and the Kenya National Bureau of Statistics (KNBS). Foreign investor data (net equity flows) are drawn from the Capital Markets Authority of Kenya quarterly statistical bulletins.

All price series are converted to continuously compounded daily log-returns: $r_t = \ln(P_t) - \ln(P_{t-1})$. Returns are then tested for stationarity using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests prior to efficiency testing. Table 1 provides descriptive statistics for key series.

Table 1: Descriptive Statistics of Daily Log>Returns (NASI and Selected Stocks), 2010–2023.

Series	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	JB Stat.	ADF (p-val.)
NASI (All-Share)	0.021	0.682	-0.312	8.441	4,218***	0.000
Equity Bank (EQTY)	0.031	1.124	-0.501	11.203	9,871***	0.000
Safaricom (SCOM)	0.058	1.371	-0.188	7.892	3,344***	0.000
KCB Group (KCB)	0.019	1.242	-0.611	12.540	11,205***	0.000

Series	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	JB Stat.	ADF (p-val.)
East African Breweries (EABL)	0.025	0.984	-0.289	9.118	5,801***	0.000
Bamburi Cement (BAMB)	-0.012	1.053	-0.447	10.234	7,312***	0.000
Kenya Power (KPLC)	-0.034	1.589	-0.831	15.122	18,903***	0.000
Co-operative Bank (COOP)	0.028	1.087	-0.392	9.663	6,540***	0.000

Note: *** denotes significance at the 1% level. JB = Jarque-Bera normality test statistic. ADF p-values are for the null of a unit root in levels (i.e., returns are stationary). Kurtosis is excess kurtosis.

Several stylized facts emerge from Table 1. All return series exhibit excess kurtosis and negative skewness, indicative of fat tails and downside risk typical of emerging-market equities (Harvey, 1995). The Jarque-Bera statistics decisively reject normality for all series, motivating the use of non-parametric and robust testing procedures. Kenya Power (KPLC) records a negative mean return over the sample, reflecting regulatory headwinds and deteriorating fundamentals during the period.

3.2 Sample Periods and Structural Breaks

Following Bai and Perron (2003), we conduct a multiple structural-break test on NASI returns to endogenously identify regime boundaries. Table 2 reports the identified break dates alongside their economic interpretations.

Table 2: Identified Structural Break Dates in NASI Daily Returns. (Bai-Perron Test)

Break Date	95% C.I.	Regime	Associated Event
Feb. 2011	Jan.–Mar. 2011	High Volatility	Inflationary crisis; CBK rate hikes
Sep. 2012	Aug.–Oct. 2012	Recovery	Monetary easing; post-election calm
Jul. 2014	Jun.–Aug. 2014	Reform	NSE demutualization; self-listing
Aug. 2017	Jul.–Sep. 2017	High Volatility	Presidential election and nullification
Mar. 2020	Feb.–Apr. 2020	Crisis	COVID-19 market closure and crash
Jan. 2021	Dec. 2020–Feb. 2021	Recovery	Vaccine rollout; fiscal stimulus

Note: Break dates identified via the Bai-Perron (2003) sequential F-test procedure with heteroscedasticity-robust standard errors. Maximum number of breaks set to 5; trimming parameter $\varepsilon = 0.10$.

4. METHODOLOGY

4.1 Static Benchmark Tests

As a benchmark, we first apply three widely used static tests. The Ljung-Box Q-test (Ljung & Box, 1978) examines joint significance of autocorrelations at lags 1 through 20. The Runs test (Wald & Wolfowitz, 1940) evaluates whether the sequence of positive and negative returns is consistent with a random process. The Lo-MacKinlay (1988) Variance Ratio (VR) test evaluates whether the variance of q -period returns scales linearly with q —a necessary condition for a random walk—using a heteroscedasticity-robust formulation.

The VR statistic for holding period q is defined as:

$$VR(q) = \text{Var}(r_t + r_{t-1} + \dots + r_{t-q+1}) / [q \times \text{Var}(r_t)]$$

Under the null of a random walk with heteroscedastic disturbances (RW3), the $Z^*(q)$ statistic follows a standard normal distribution asymptotically. We test $q \in \{2, 4, 8, 16\}$ following convention (Lo & MacKinlay, 1988).

4.2 Rolling-Window Variance Ratio Tests

To capture time variation in efficiency, we implement rolling-window VR tests following Kim, Shamsuddin and Lim (2011). A fixed rolling window of width $w = 260$ trading days (approximately one calendar year) is rolled forward one day at a time across the full sample. At each window endpoint t , we compute the Chow-Denning (1993) joint VR statistic across $q \in \{2, 4, 8, 16\}$:

$$CD = \max\{|Z^*(2)|, |Z^*(4)|, |Z^*(8)|, |Z^*(16)|\}$$

Rejection of the random walk at a given window is recorded when CD exceeds its critical value at the 5% significance level. The proportion of rolling windows rejecting the null (rejection frequency) serves as our primary measure of inefficiency. A higher rejection frequency corresponds to a greater degree of predictability and thus lower efficiency.

4.3 Automatic Variance Ratio (AVR) Test

To mitigate the bias from a priori selection of holding periods q , we additionally implement the Automatic Variance Ratio (AVR) test of Kim (2009), which selects q optimally using data-dependent bandwidth selection criteria analogous to Andrews (1991). The AVR test statistic is:

$$AVR = \int_0^1 [VR(q(h)) - 1]^2 dh$$

where $q(h)$ is determined by minimizing an asymptotic mean-squared error criterion. The AVR test is asymptotically standard normal under the null and is robust to conditional heteroscedasticity and non-normality.

4.4 Generalised Spectral (GS) Test

We employ the Generalised Spectral (GS) test of Escanciano and Velasco (2006) as a comprehensive nonlinear dependence test. Unlike linear autocorrelation-based tests, the GS test can detect both linear and nonlinear serial dependencies in the return series, including GARCH-type conditional heteroscedasticity and regime-switching patterns. The GS test statistic is based on the empirical characteristic function and converges to a functional of Brownian motion under the martingale difference null.

4.5 Panel Determinants of Efficiency

To identify the drivers of time-varying efficiency, we construct a panel dataset where the dependent variable is the binary inefficiency indicator $D_{it} = 1$ {rolling-window VR test rejects for stock i in month t }. We estimate a panel logit model with fixed effects:

$$\Pr(D_{it} = 1) = \Lambda(\alpha_i + \beta_1 \text{Volume}_{it} + \beta_2 \text{ForeignFlow}_t + \beta_3 \text{MktCap}_{it} + \beta_4 \text{Inflation}_t + \beta_5 \text{VIX}_t + \varepsilon_{it})$$

where $\Lambda(\cdot)$ is the logistic function, α_i is a stock fixed effect, Volume_{it} is log average daily trading volume, ForeignFlow_t is net monthly foreign equity inflows scaled by total market capitalisation, MktCap_{it} is log market capitalisation, Inflation_t is the year-on-year CPI inflation rate, and VIX_t is the CBOE Volatility Index as a proxy for global risk appetite. Standard errors are clustered at the stock level.

5. EMPIRICAL RESULTS

5.1 Static Tests

Table 3 presents results from the static benchmark tests applied to the full-sample NASI returns and the eight representative stocks listed in Table 1.

Table 3: Static Weak-Form Efficiency Tests — Full Sample. (2010–2023)

Series	LB Q(20)	Runs stat	Z-	VR(2) Z*	VR(4) Z*	VR(8) Z*	VR(16) Z*	Reject RW?
NASI	42.31***	-3.21***		3.88***	3.12***	2.44**	1.87*	Yes
EQTY	28.54**	-2.14**		2.91***	2.33**	1.98**	1.55	Yes
SCOM	19.73*	-1.55		1.87*	1.43	1.12	0.88	Marginal
KCB	35.62***	-2.98***		3.21***	2.67***	2.11**	1.74*	Yes
EABL	21.45**	-1.82*		2.11**	1.78*	1.44	1.10	Yes

Series	LB Q(20)	Runs Z-stat	VR(2) Z*	VR(4) Z*	VR(8) Z*	VR(16) Z*	Reject RW?
BAMB	31.87***	-2.56**	2.77***	2.31**	1.89*	1.52	Yes
KPLC	48.22***	-3.87***	4.11***	3.55***	2.98***	2.44**	Yes
COOP	26.41**	-2.03**	2.55**	2.04**	1.67*	1.31	Yes

Note: ***, **, * denote significance at 1%, 5%, and 10% levels respectively. LB Q(20) is the Ljung-Box statistic with 20 lags. Z* are heteroscedasticity-robust variance ratio statistics under the RW3 null. Reject RW? is based on the Chow-Denning joint test.

The static tests paint a consistent picture: the NASI and most individual stocks reject the random walk null over the full sample, with the exception of Safaricom (SCOM), which shows only marginal predictability. This finding aligns with prior literature (Olweny & Kimani, 2011; Muthama & Mutohya, 2013). However, the full-sample rejection masks considerable heterogeneity across sub-periods, as the rolling-window analysis reveals.

5.2 Rolling-Window Results

Figure 1 (not reproduced here) plots the rolling Chow-Denning statistic over time for the NASI. The statistic breaches the 5% critical value during three distinct episodes: (i) February 2011 to November 2012, corresponding to the inflationary crisis and post-crisis recovery; (ii) July to October 2017, surrounding the contested presidential election; and (iii) March to September 2020, coinciding with the COVID-19 market shock. Outside these windows, the CD statistic generally falls below the critical value, consistent with approximate weak-form efficiency.

Table 4 summarises the rolling-window rejection frequencies across the six identified regimes from Table 2.

Table 4: Rolling-Window Rejection Frequencies by Market Regime.

Regime	Period	Obs.	Rej. Freq. (NASI)	Mean CD	AVR p-value	GS p-value
Pre-Inflationary	Jan. 2010–Jan. 2011	261	18.4%	1.52	0.147	0.183
Inflationary Crisis	Feb. 2011–Aug. 2012	393	71.2%	3.88***	0.001	0.002
Post-Crisis Recovery	Sep. 2012–Jun. 2014	460	22.7%	1.64	0.098	0.124
Post-	Jul. 2014–	785	14.9%	1.31	0.187	0.211

Regime	Period	Obs.	Rej. Freq. (NASI)	Mean CD	AVR p-value	GS p-value
Demutualization	Jul. 2017					
Election & COVID	Aug. 2017– Dec. 2020	871	58.3%	3.11***	0.004	0.008
Post-COVID Recovery	Jan. 2021– Dec. 2023	757	19.2%	1.58	0.121	0.156

Note: Rejection frequency is the proportion of rolling windows (width = 260 days) for which the Chow-Denning statistic exceeds its 5% critical value. Mean |CD| is the time-average of the absolute Chow-Denning statistic. AVR and GS tests applied to regime sub-samples. *** $p < 0.01$.

The results in Table 4 are strikingly supportive of the AMH. Rejection frequencies are high (>50%) during the inflationary crisis and election/COVID regimes but fall to below 20% in calmer periods. The post-demutualization regime (July 2014 to July 2017) records the lowest rejection frequency (14.9%), suggesting that the structural reforms accompanying NSE's self-listing improved market quality and information processing capacity, consistent with the findings of Karuitha, Onyuma and Mugo (2013) for other event-driven efficiency improvements on the NSE.

5.3 AVR and Generalised Spectral Test Results

The AVR test, which avoids preselection of q , corroborates the rolling-window findings. For the inflationary crisis and election/COVID regimes, the AVR rejects the martingale null at the 1% level ($p = 0.001$ and $p = 0.004$ respectively). In contrast, the post-demutualization regime yields an AVR p-value of 0.187, providing no evidence against the random walk.

The GS test, which additionally captures nonlinear serial dependence, shows a pattern closely tracking the AVR results. Notably, the GS test p-values are marginally smaller than the AVR p-values across all regimes, suggesting the presence of some nonlinear predictability—potentially GARCH-type volatility clustering—even in relatively efficient regimes. However, this nonlinear dependence does not appear to be economically exploitable given the transaction costs prevailing on the NSE.

5.4 Panel Determinants of Efficiency

Table 5 presents panel logit estimates of the determinants of time-varying inefficiency across the 25 stocks over the 2010–2023 period.

Table 5: Panel Logit Estimates — Determinants of Weak-Form Inefficiency. ($D_{it} = 1$)

Variable	Coeff.	Std. Err.	z-stat	p-value	Marginal Effect
Log Trading Volume	-0.312	0.087	-3.58	0.000***	-0.048
Foreign Investor Flow (%MktCap)	-1.841	0.534	-3.45	0.001***	-0.285
Log Market Capitalisation	-0.274	0.092	-2.98	0.003***	-0.042
CPI Inflation (y-o-y, %)	0.218	0.067	3.25	0.001***	0.034
CBOE VIX Index	0.041	0.019	2.18	0.029**	0.006
Constant	3.451	0.821	4.20	0.000***	—
Stock Fixed Effects	Yes	—	—	—	—
Obs. (stock-months)	3,600	—	—	—	—
McFadden R ²	0.231	—	—	—	—

Note: Standard errors clustered at the stock level. Marginal effects evaluated at the sample mean of all continuous variables. ***, ** denote significance at 1% and 5% levels.

All five determinants are statistically significant with the expected signs. Higher trading volume, greater foreign investor participation, and larger market capitalisation are associated with lower probability of inefficiency (i.e., higher efficiency), consistent with the liquidity-efficiency nexus documented by Chordia, Roll and Subrahmanyam (2008). A one-standard-deviation increase in log trading volume reduces the probability of inefficiency by approximately 4.8 percentage points, while a comparable increase in the foreign investor flow ratio reduces it by 28.5 percentage points—the largest marginal effect in the model. This finding underscores the informational role of sophisticated cross-border investors in price discovery on frontier markets (Bae, Ozoguz, Tan & Wirjanto, 2012).

Conversely, higher inflation and global risk aversion (VIX) increase the probability of return predictability, consistent with the hypothesis that macroeconomic instability disrupts price discovery mechanisms and creates opportunities for behavioral biases to drive prices away from fundamentals (De Long, Shleifer, Summers & Waldmann, 1990).

6. DISCUSSION AND POLICY IMPLICATIONS

Our results offer several insights for theory, practice, and regulation. From a theoretical standpoint, the pronounced time-variation in efficiency documented here is inconsistent with the static EMH but directly predicted by Lo's (2004) Adaptive Markets Hypothesis. The NSE appears to follow evolutionary efficiency dynamics: competition among arbitrageurs pushes

prices toward the random walk during stable regimes, but exogenous shocks temporarily create exploitable patterns as market participants adapt to new information environments. This is consistent with Urquhart and Hudson's (2013) AMH evidence for developed markets and extends this line of inquiry to East African frontier markets.

For portfolio managers and technical analysts, our findings imply that the profitability of momentum and mean-reversion strategies on the NSE is likely to be episodic rather than persistent. Strategies calibrated to crisis periods—when autocorrelation is high—may be profitable within those windows but should be abandoned as markets normalise. The rolling-window rejection frequency provides a real-time efficiency barometer that practitioners could use to time the deployment of active versus passive investment approaches.

For policymakers and the Capital Markets Authority (CMA), the positive association between foreign investor participation and efficiency supports continued efforts to attract cross-border institutional capital. The NSE's 2023 initiative to reduce settlement cycles from T+3 to T+2 and the planned introduction of securities lending are steps likely to further improve market microstructure. Our findings suggest that reforms specifically targeting trading activity and foreign investor access may yield the largest efficiency dividends.

The negative relationship between inflation and efficiency points to the importance of macroeconomic stability for capital market development. During the 2011 inflationary episode when CPI exceeded 19%, predictability in NSE returns was at its highest. This suggests that the Central Bank of Kenya's inflation-targeting framework not only serves its primary price stability mandate but also has positive secondary effects on capital market efficiency.

7. CONCLUSION

This study has investigated weak-form market efficiency on the Nairobi Securities Exchange using a time-varying methodology applied to daily data from 2010 to 2023. Our primary findings are threefold. First, the NSE is not uniformly inefficient: efficiency varies substantially across regimes, with crisis periods characterised by high predictability and tranquil periods approximating the random walk. Second, structural developments—particularly the 2014 demutualization—are associated with measurable efficiency improvements, suggesting that market microstructure reforms matter for informational quality. Third, trading activity, foreign investor participation, and market capitalisation are the dominant positive determinants of efficiency, while macroeconomic instability undermines the random-walk property.

These findings have important implications for how regulators, practitioners, and academics should conceptualise efficiency in frontier and emerging markets. Rather than treating efficiency as a fixed attribute to be confirmed or rejected in a single test, the evidence supports a dynamic view consistent with the Adaptive Markets Hypothesis. Future research could extend this framework to alternative asset classes traded on the NSE, including government bonds, real estate investment trusts (REITs), and exchange-traded funds (ETFs), as well as applying high-frequency data as tick data becomes increasingly available.

A limitation of the present study is that our rolling-window approach, while capturing regime-level variation, may smooth over day-level efficiency dynamics that would be visible only with higher-frequency data. Additionally, the panel logit model identifies associations rather than causal mechanisms; future work employing natural experiments—such as the staggered introduction of mobile trading across investor segments—could provide sharper causal identification.

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