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NEPAL RASTRA BANK

Time-Varying Efficiency and Volatility Regimes in Nepal Stock Exchange (NEPSE): Evidence from Daily Data under the Adaptive Market Hypothesis

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ABSTRACT
This study evaluates the Adaptive Market Hypothesis (AMH) in the Nepalese stock market using daily index returns from July 1995 to February 2025, representing nearly three decades and the longest high-frequency analysis of the market to date. Comprehensive efficiency diagnostics reveal clear time-varying dynamics: persistent inefficiency from 1999 to 2019 is followed by emerging signs of efficiency from 2021 to 2025, coinciding with financial digitization and regulatory reforms. Employing GARCH and Markov-switching models, the results indicate highly persistent volatility ($\alpha + \beta \approx 0.90$) and the presence of two distinct volatility regimes. Low-volatility states persist for approximately 15 trading days, whereas high-volatility episodes last around 9 days, and are associated with major macroeconomic shocks, including the 2015 earthquake and the COVID-19 pandemic. Unlike developed markets, NEPSE does not exhibit a statistically significant leverage effect ($\gamma_1 = 0.0279$, $p = 0.120$), suggesting symmetric volatility responses to positive and negative shocks. These findings contradict the assumption of static market efficiency and provide empirical evidence in support of the AMH's prediction of evolving efficiency in emerging markets. The results carry important implications for regime- dependent investment strategies and countercyclical regulatory policies during high-volatility states.

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I. Introduction

Financial markets, where securities such as stocks, bonds, commodities, and derivatives are traded, do not remain perfectly efficient over time. Building on Lo's (2004, 2005) Adaptive Market Hypothesis (AMH), which integrates the principles of evolution and behavioral finance, this study investigates how the Nepalese stock market adapts to dynamic economic environments. The AMH extends the Efficient Market Hypothesis (EMH) (Fama, 1970), which assumes that asset prices reflect all available information, by proposing that efficiency evolves as investors learn, adapt, and respond to market conditions. In contrast to the static rationality assumed by the EMH, behavioral finance highlights how cognitive biases, emotions, and social influences create departures from efficiency (Kahneman &

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Tversky, 1979; Barberis & Thaler, 2003). The AMH reconciles these views by suggesting that markets alternate between efficient and inefficient phases depending on environmental pressures and informational shocks.

Extensive international evidence demonstrates that market efficiency is time-varying rather than constant (Kim et al., 2011; Lim et al., 2013; Urquhart & Hudson, 2013; Ghazani & Araghi, 2014). The Nepal Stock Exchange (NEPSE) provides a compelling context for evaluating this adaptability. Established in 1993, NEPSE remains relatively small, volatile, and dominated by retail investors. As of mid-January 2025, the market hosts approximately 267 listed firms, records an average daily turnover of around NPR 5.21 billion, and often experiences sentiment-driven trading rather than fundamentals-based decision-making (NEPSE Monthly Report, Poush 2081).

Earlier studies (Dangol, 2012; Jha & Dhungana, 2021; Joshi, 2024) find evidence against the weak-form EMH for the NEPSE, attributing inefficiency to low liquidity, limited information transparency, and herding behavior. To address methodological limitations in existing research, this study employs daily NEPSE index data from July 1995 to February 2025. High-frequency data allow for a granular assessment of evolving efficiency, volatility clustering, and market responses to shocks, especially during significant events such as political transitions, the 2015 Earthquake, and the COVID-19 pandemic. This approach enables a precise evaluation of how market conditions shift across different regimes.

This study was guided by the following hypotheses:

- **H_0:** NEPSE returns follow a random walk, indicating no adaptive behavior or predictable structure.
- **H_1:** The NEPSE exhibits time-varying efficiency consistent with the AMH.

Despite growing international evidence supporting the AMH, empirical testing on NEPSE remains limited in two critical ways. First, previous studies (Dangol, 2012, 2016; Jha & Dhungana, 2021; Joshi, 2024) have predominantly relied on monthly data or observation periods shorter than 10 years, which may obscure the short-term dynamics and volatility clustering central to the AMH framework. Second, no prior research has employed regime-switching models to formally identify and characterize distinct volatility states in NEPSE. This study addresses these gaps by employing nearly three decades (1995-2025) of daily return data combined with GARCH-family models and Markov-switching frameworks to provide the first comprehensive, high-frequency analysis of adaptive market behavior in Nepal.

By empirically evaluating these hypotheses, this study provides the first long-term, daily data-based evidence of adaptive behavior in Nepal's stock market. The findings contribute to understanding how emerging markets evolve under uncertainty and provide regulators and policymakers the opportunity to enhance market stability, transparency, and investor protection.

II. Literature Review

The concept of market efficiency has long-shaped financial economics, emphasizing that asset prices incorporate all available information. Early formulations of the random walk hypothesis by Regnault (1893), Bachelier (1900), and later Samuelson (1965) laid the foundation for the Efficient Market Hypothesis (EMH). Fama (1965) provided comprehensive empirical evidence that stock price changes behave as independent random variables, demonstrating that chart reading and technical analysis based on past price patterns provider no predictive power—a finding that directly informed the formalization of market efficiency. Fama (1970) subsequently formalized the EMH in weak, semi-strong, and strong forms, proposing that prices fully incorporate past information, including public news and inside information. Under this framework, return prediction is impossible because latest information is immediately incorporated into prices. However, persistent anomalies, including momentum effects, calendar patterns, and size premiums, challenge the assumption of constant efficiency. Fama (1991), reviewing two decades of market efficiency research, acknowledged these anomalies while noting the joint-hypothesis problem—that tests of market efficiency are simultaneously evaluating an underlying pricing model, complicating interpretation of rejections. Events such as the dot-com bubble and the 2008 global financial crisis further illustrate that prices can deviate significantly from fundamentals. Behavioral economists attribute these deviations to systematic cognitive biases, including herding behavior, overconfidence, and loss aversion—that violate EMH's rationality assumptions (Kahneman & Tversky, 1979; Shefrin & Statman, 2000). These insights suggest markets do not always operate rationally or efficiently.

To reconcile rational efficiency theory with behavioral irregularities, Lo (2004, 2005) introduced the Adaptive Market Hypothesis (AMH). The AMH proposes that market efficiency is not static but evolves as investors learn, compete, and adapt to environmental and economic changes. During stable periods, markets may appear efficient, and during periods of stress or innovation, inefficiencies may emerge as investors adjust their strategies. Therefore, predictability is not permanent but episodic, which is consistent with the evolutionary learning process. Recent theoretical work by Lo and Zhang (2024) further formalizes the mathematical basis of the AMH using evolutionary models, demonstrating how seemingly rational and seemingly inefficient behaviors can coexist through natural selection mechanisms. This framework has proven valuable for understanding phenomena ranging from business strategy design to financial crisis prediction.

There is substantial empirical research supporting this adaptive approach across different market types. Studies in developed markets (Kim et al., 2011; Lim et al., 2013; Urquhart & Hudson, 2013) report that return predictability becomes stronger and weaker over time. Urquhart and McGroarty (2016) extend this evidence by examining major global indices (S&P 500, FTSE 100, NIKKEI 225, and EURO STOXX 50) using bootstrapped variance ratio tests combined with BDS tests on AR-GARCH whitened returns, demonstrating that nonlinear predictability persists even after accounting for conditional heteroscedasticity—a finding that validates the methodological combination of GARCH models with nonlinear dependence tests. More recently, Noreen et al. (2022) introduced investor myopic loss aversion as a new proxy to assess AMH on the NYSE (1994–2020), finding that market efficiency varies with changes in investor behavior, with notable adaptations observed in particular during the 2000–2001 and 2007–2009 periods. Research in emerging economies such as India, China, and Pakistan confirms similar patterns, linking adaptive efficiency to financial reform and maturity (Hiremath & Kumari, 2014; Khuntia & Pattanaik, 2018; Xiong et al., 2019). Munir et al. (2022) extended this analysis to South Asian markets, demonstrating that contrarian profitability varies with market conditions, where market conditions—rather than volatility—serve as the primary predictor, which is different from developed market patterns.

Rönkkö et al. (2024) provide particularly relevant insights for small markets like NEPSE, demonstrating through subsample and rolling window analysis that small market size alone does not predetermine inefficiency. Their Finnish market study reveals that foreign investor access improves efficiency with a delay, and that volatility-return relationships vary temporally in ways inconsistent with traditional models. These findings suggest structural reforms—rather than market scale—drive adaptive efficiency in emerging markets.

The COVID-19 pandemic provided a natural experiment to evaluate AMH predictions. Okorie and Lin (2021) found divergent efficiency trajectories across major markets: India became less efficient while Russia improved, while the US and Brazilian markets showed stability, illustrating how the same shocks can produce heterogeneous adaptive responses depending on market structure. Evidence from African markets (Obalade & Muzindutsi, 2019b; Adaramola & Adekanmbi, 2020), cryptocurrency markets (Karasiński, 2023), and Latin America (Cruz-Hernández & Mora-Valencia, 2024) further shows that calendar anomalies and structural dependencies appear and disappear depending on prevailing conditions. Cruz-Hernández and Mora-Valencia (2024) demonstrated using multiple variance ratio tests and GARCH-M modeling that calendar anomalies in Latin American indices arise and dissipate depending on prevailing conditions and significant news events, which is consistent with AMH's prediction of time-varying market behavior.

Empirical tests of EMH and AMH often rely on models capable of capturing nonlinearity, volatility clustering, and regime shifts. Models of the GARCH family are widely used to assess conditional heteroskedasticity and volatility persistence (Cruz-Hernández & Mora-Valencia, 2024), while GARCH-M specifications enable direct testing of time-varying risk-return relationships under the AMH framework. Markov-switching models detect transitions between low- and high-volatility states, while more recent approaches incorporate behavioral proxies such as myopic loss aversion to capture investor adaptation (Noreen et al., 2022). Complementary tests—including variance ratio tests, BDS tests, and generalized spectral tests (Cruz-Hernández & Mora-Valencia, 2024; Okorie & Lin, 2021)—provide robust checks for martingale difference properties and nonlinear dependencies. Rönkkö et al. (2024) used a combination of linear and nonlinear predictive tests to show that subsample and rolling window approaches are particularly effective in detecting time-varying efficiency. These models align directly with AMH principles: they allow efficiency to vary over time and enable the identification of structural breaks and behavioral changes.

Existing studies on NEPSE present mixed evidence. Dangol (2012, 2016) documents weak-form inefficiency, while Jha and Dhungana (2021) find evidence of gradual improvement using linear and nonlinear tests. Joshi (2024) highlights fluctuations in efficiency linked to political and economic constraints, which indicate adaptive behavior. Research on seasonal and calendar effects, such as day of the week and holiday anomalies (Shrestha & Poudel, 2019; Thapa, 2020), shows that these patterns tend to emerge and fade over periods, reflecting changing investor sentiment. Furthermore, macroeconomic factors such as policy rates, remittance flows, and political instability have been shown to influence returns (Adhikari & Giri, 2021; Pandey, 2020; Thapa, 2025).

The existing body of research suggests that the Nepalese stock market does not maintain constant efficiency but exhibits context-dependent and time-varying behavior more closely aligned with the AMH framework than with the static assumptions of EMH.

III. Trends of Major Variables

This section presents the trends and descriptive characteristics of daily NEPSE index from July 1995 to February 2025, providing preliminary evidence of time-varying market behavior before formal econometric modelling.

3.1 Historical Market Performance

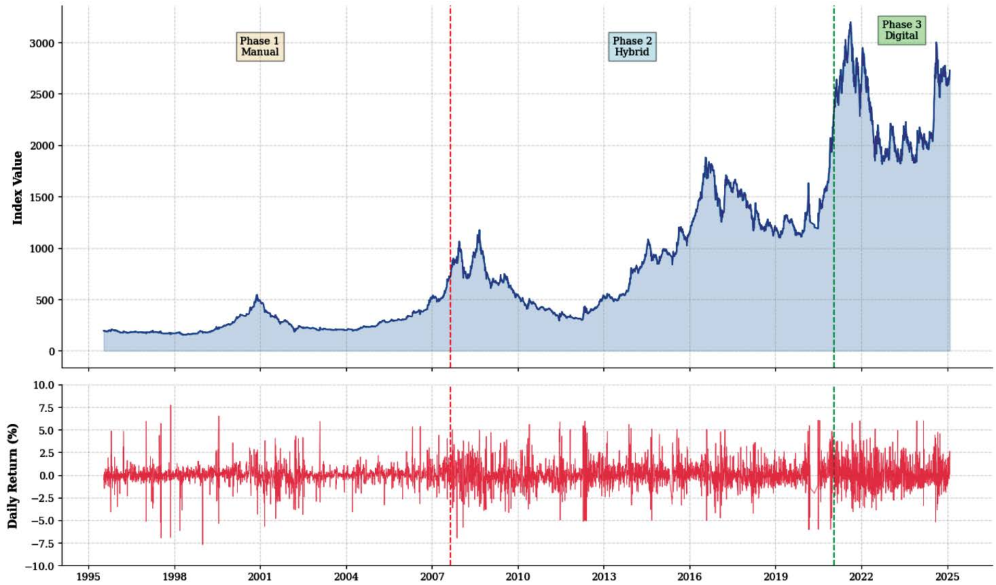
Figure 1 illustrates a comprehensive two-panel visualization of NEPSE's evolution over three decades. The upper panel presents the index level, while the lower panel displays corresponding daily returns, enabling simultaneous examination of index trends and volatility dynamics across three distinct technological eras.

NEPSE, Nepal's only stock exchange, experienced two major technological transformationsa that fundamentally changed market structured. Screen-based trading in August 2007 under the ADB-supported Capital Market Development Program. Subsequently, the NEPSE Online Trading System (NOTS) was launched in November 2018, and became fully automated on 17 January 2021 (Vaidya, 2021). The COVID-19 pandemic further accelerated the adoption of online trading, expanding remote market access and increasing investor participation. The index demonstrates distinct cyclical movements over time.

Three distinct phases emerge:

- **Phase 1 (1995-2007):** Index ranged 100-550 points with moderate volatility. Limited participation and physical trading constraints.
- **Phase 2 (2007-2021):** Gradual expansion from 200 to 3,200 points (August 2021peak), accelerating post-2018 NOTS launch. Major events: 2008 crisis, 2015 earthquake, COVID-19 bull market.
- **Phase 3 (2021-2025):** High volatility with rapid oscillations (1,800-2,500 points) following monetary tightening. Persistent clustering reflects digital market dynamics.

The lower panel reveals pronounced volatility clustering across all phases. Phase 1 exhibited occasional extremes; Phase 2 showed increasing dispersion post-2018; Phase 3 displays persistent high-frequency volatility with frequent extreme events. The synchronization of structural breaks across both panels suggests market dynamics evolved with technological changes, providing a descriptive basis for the subsequent empirical analysis.



Source: NEPSE Adjusted Data

Figure 1: NEPSE Historical Performance & Volatility (1995 -2025)

3.2 *Descriptive Statistics*

Table 1 provides the descriptive statistics for the full sample and the 15 two-year subsamples of the index's daily returns. The full sample mean daily return is relatively low (0.039%), while standard deviation (1.213%) indicates substantial volatility. Distributional properties deviate markedly from normality: positive skewness (0.164) and excess kurtosis (5.463) indicate heavy tails, with the Jarque–Bera statistic strongly rejecting normality.

Table 1: Descriptive Statistics of NEPSE Daily Returns

Period	Obs.	Mean	Median	Max.	Min.	SD.	Skewness	Kurtosis	Jarque-Bera
Full sample	6794	0.00039	0.00004	-0.08014	0.07457	0.01213	0.16353	5.46287	8478.3280
1995-07/1997-06	474	-0.00012	-0.00020	-0.05281	0.05774	0.00840	0.59011	15.90741	5025.1640
1997-07/1999-06	468	0.00032	0.00074	-0.08014	0.07457	0.01007	-2.50750	31.98058	20434.2000
1999-07/2001-06	472	0.00092	0.00100	-0.05870	0.06327	0.01088	-0.15627	9.29439	1700.8390
2001-07/2003-06	479	-0.00100	-0.00072	-0.04936	0.05766	0.01118	0.31841	5.68878	653.9899
2003-07/2005-06	444	0.00070	0.00096	-0.04156	0.02138	0.00580	-1.52307	10.23341	2109.0310
2005-07/2007-06	447	0.00166	0.00102	-0.03246	0.05224	0.00905	0.98177	5.95408	732.0860
2007-07/2009-06	460	0.00025	-0.00020	-0.07224	0.04902	0.01587	-0.27046	1.35986	41.0514
2009-07/2011-06	451	-0.00150	-0.00206	-0.05117	0.05703	0.01249	0.69318	4.57893	430.1146
2011-07/2013-06	457	0.00084	-0.00064	-0.05270	0.05790	0.01443	0.40242	4.51495	400.4949

Period	Obs.	Mean	Median	Max.	Min.	SD.	Skewness	Kurtosis	Jarque-Bera
2013-07/2015-06	444	0.00147	0.00051	-0.05131	0.05459	0.01164	0.51832	4.07315	326.8055
2015-07/2017-06	463	0.00108	0.00047	-0.05163	0.04920	0.01280	0.23834	3.01260	179.4697
2017-07/2019-06	475	-0.00048	-0.00092	-0.04337	0.03552	0.00982	0.50308	2.07027	104.8631
2019-07/2021-06	428	0.00191	0.00107	-0.06229	0.05889	0.01548	-0.18058	3.85119	266.8241
2021-07/2023-06	470	-0.00058	-0.00145	-0.04142	0.05835	0.01558	0.49966	0.85192	33.7694
2024-07/2025-02	135	0.00217	0.00136	-0.05328	0.04617	0.01616	0.08639	0.93746	5.1113

Note: Daily returns (), calculated as: . Mean, median, max, min and standard deviation reported in decimal form; multiply by 100 for percentages.

Subperiods analysis reveals considerable heterogeneity. Periods such as 1997–1999 (skewness: -2.51, kurtosis: 31.98) and 2003-2005 (kurtosis: 10.23) exhibit extreme asymmetric and fat tails, indicating episodic market turbulence. Volatility varies substantially across subsamples, with elevated standard deviation during periods such as 2007–2009(1.587%), 2019–2021 (1.548%), and 2021–2023 (1.558%), reflecting crisis periods and structural transitions. The Jarque–Bera statistic rejects normality in all subperiods, confirming persistent non-normal behavior.

These patterns indicate time-varying volatility, changing higher-moment characteristics, and evolving return dynamics, key features motivating GARCH and Markov-Switching model analysis.

V. Research Methodology

Building on the identified trends and descriptive patterns, this section provides the econometric framework employed to formally evaluate the AMH in NEPSE.

4.1 Data Description

This study employs quantitative research design to examine AMH in the Nepalese stock market. The analysis uses daily adjusted closing values of the NEPSE Index from July 17, 1995, to February 3, 2025, obtained from the NEPSE, Securities Board of Nepal (SEBON) and Nepal Rastra Bank (NRB).

To capture the evolving nature of market behavior, two complementary approaches were adopted: subsample and rolling-window analyses. In the subsample approach, the dataset was divided into 15 two-year intervals to observe temporal variations in market adaptability. The rolling-window method employed a five-year window, corresponding roughly to Nepal's macroeconomic and political cycles (e.g., government terms and policy horizons). This length ensures sufficient observations for estimation while allowing for a meaningful dynamic interpretation.

Daily returns, R_t, were calculated using the logarithm function, expressed as:

$$R_t = [ln\ (P_t) - ln\ (P_{t-1})] \qquad (1)$$

where, P_t and P_{t-1} indicate the price index at periods t and $t-1$, respectively.

4.2 Data Processing and Stationarity

Non-trading days were excluded from the dataset to ensure continuity in the return series. Extreme observations were winsorized at the 1^{st} and 99^{th} percentiles to minimize the influence of outliers while preserving the integrity of the data. After cleaning, no missing values were detected. Before proceeding with econometric modelling, we must first confirm that returns satisfy the stationarity requirement underlying these techniques. Although financial log returns are typically stationary by construction, formal statistical testing is necessary to confirm this property empirically. To ensure robustness, three complementary unit root tests were employed: The Augmented Dickey–Fuller (ADF) (Dickey & Fuller, 1979), Phillips–Perron (PP) (Phillips & Perron, 1988), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) (Shin, & Schmidt, 1992) tests. The ADF and PP tests examine the null hypothesis of a unit root (non-stationarity), whereas the KPSS test assumes stationarity as the null hypothesis, thereby providing complementary evidence. All tests were implemented in Python using the *statsmodels* library.

4.3 Preliminary Tests for Market Efficiency

To justify the application of the AMH framework, several commonly used market efficiency diagnostics were conducted. The Ljung–Box test (Ljung & Box, 1978) assessed serial correlation, the Runs test (Wald & Wolfowitz, 1940) evaluated the randomness of return sequences, and the Variance Ratio test (Lo & MacKinlay, 1988) tested for random-walk behavior. For all tests, statistical significance was evaluated at the 1%, 5%, and 10% levels. Periods with insignificant results were classified as weak-form efficient, while significant results at any of these levels interpreted as evidence of market inefficiency.

All non-linear tests were conducted on pre-whitened return series. Volatility dependence was assessed using the ARCH–LM test (Engle, 1982) and McLeod–Li test (McLeod & Li, 1983), where significant results ($p < 0.05$) indicated volatility inefficiency. Higher-order nonlinear dependence was evaluated using the Brock–Dechert–Scheinkman (BDS) test (Brock et al., 1996), with insignificant outcomes ($p \geq 0.05$) interpreted as market efficiency under the AMH framework.

As these procedures follow established practice, their mathematical equations are provided in Appendix A. Together, these tests provide a comprehensive assessment of linear dependence, heteroscedasticity, and nonlinear structure—key dimensions of adaptive market behavior.

4.4 Econometric Modelling Framework

4.4.1 GARCH Model

To examine time-varying volatility, this study employs the GARCH (1,1) model of Bollerslev (1986), which captures conditional heteroskedasticity and persistence in daily returns. The model is specified as:

Mean Equation

$$r_t = \mu + \varepsilon_t \qquad \varepsilon_t = \sigma_t z_t \tag{2}$$

where $z_t \sim N(0,1)$.

Variance Equation

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{3}$$

where ω > 0 ensures positivity, α ≥ 0 captures the short-run reaction of volatility to shocks, and β ≥ 0 measures volatility persistence. The sum of the parameters (measures volatility persistence and therefore provides insight into how long shocks continue to affect the market. Values approaching unity indicate high persistence.

4.4.2 EGARCH Model

Because emerging markets often exhibit asymmetric volatility responses, the baseline specification was augmented with the Exponential GARCH (EGARCH) model of Nelson (1991) to evaluate whether negative shocks generate stronger volatility reactions than positive shocks. The EGARCH conditional variance equation is:

$$ln(\sigma_t^2) = \omega + \beta ln(\sigma_{t-1}^2) + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \sigma t-1 + \gamma\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \tag{4}$$

where:

- the logarithmic specification ensures $\sigma_t^2 > 0$ without parameter restrictions,
- α measures the magnitude effect of shocks,
- γ captures asymmetry or the leverage effect as follows:
  - If γ < 0: negative shocks increase volatility more than positive shocks,
  - If γ = 0: the response to positive and negative shocks is symmetric.

4.4.3 Markov-Switching Model

To identify structural breaks and regime changes in market dynamics, a two-state Markov-Switching (MS) model, Hamilton (1989) was used. The model allows the data to switch between the unobserved regimes:

- *Regime 0:* Low volatility/Calm state
- *Regime 1:* High volatility/Turbulent state

The MS model is expressed as:

Observation (Mean) Equation

$$r_t = \mu_{st} + \varepsilon_t, \ \varepsilon t \sim N(0, \sigma_{st}^2) \tag{5}$$

where

- r_t is the log return at time t,
- $s_t \in \{0,1\}$ denotes the latent regime,
- μ_{st} and σ_{st}^2 are the regime-dependent mean and variance parameters, respectively.

Markov Transition Process

The regime variable s_t follows a first-order Markov chain with transition probabilities:

$$P = (p_{00} \;\; p_{01} \;\; p_{10} \;\; p_{11}) \tag{6}$$

where, $P_{ij} = \Pr(s_t - j \mid s_{t-1} - i)$, i, j∈ {0,1}.

Expected Regime Duration

The expected duration of regime i is computed as:

$$D_i = \frac{1}{1 - P_{ii}} \tag{7}$$

which provides insights into the stability of the market.

The estimated transition probabilities provide the likelihood of remaining in or moving between regimes, enabling the calculation of the expected regime duration, a key indicator of market stability.

4.4.4 Sequential Implementation Strategy

The modelling approaches were implemented sequentially to provide complementary insights into market dynamics.

1. **Step 1:** The GARCH and EGARCH models estimate conditional volatility and persistence, quantifying the degree of volatility clustering and asymmetry in NEPSE returns.
2. **Step 2:** The Markov-Switching models identify structural breaks and volatility regimes, distinguishing periods of relative market efficiency (low volatility) from periods of instability (high volatility).

This sequential framework directly evaluates the AMH's core premise: if market efficiency evolves over time, we should observe (1) time-varying volatility (GARCH evidence) and (2) distinct regime shifts corresponding to changes in market conditions and investor behavior (Markov-Switching evidence).

Together, these models provide a comprehensive test of adaptive efficiency in NEPSE.

Results and Discussion

This section provides findings from stationarity confirmation, efficiency diagnostics, volatility modeling, and regime-switching analysis. Results are interpreted through AMH, with emphasis on economic implications for investors and policymakers.

5.1 Stationarity Confirmation

Formal stationarity tests (ADF, PP, and KPSS) were applied to daily returns to examine the properties of the data. The ADF and PP tests produced highly negative t-statistics (-21.68 and -71.81 respectively, for the constant with trend model) that far exceeded the 1% critical values (-3.96), strongly rejecting the null hypothesis of a unit root. The KPSS statistics which reverses the null hypothesis, yielded a test statistic (0.095) well below the 1% critical threshold (0.739), failing to reject the null of stationarity. Results remain consistent across both specifications—constant only and constant with trend—confirming robustness. Collectively, these tests unanimously confirm that daily returns are stationary, validating their use in subsequent GARCH, EGARCH, and Markov-Switching models and ensuring that econometric inferences are not subject to spurious regression problems.

Table 2: Unit Root test of Daily returns

	t-statistic	1%	5%	10%
Augmented Dickey-Fuller test				
Model 1: Constant with Trend	-21.681584	-3.960	-3.411	-3.127
Model 2: Only Constant	-21.675598	-3.431	-2.862	-2.567
Phillips-Perron test				
Model 1: Constant with Trend	-71.814999	-3.9601033266	-3.41136508	-3.127430712
Model 2: Only Constant	-71.828334	-3.4313130167	-2.861965573	-2.566996529
Kwiatkowski–Phillips–Schmidt–Shin test	0.094934	0.739	0.463	0.347

5.2 Market Efficiency Diagnostics

5.2.1 Linear Efficiency Diagnostics

Table B.1 presents comprehensive linear efficiency diagnostics across 15 two-year subsamples. The full-sample Ljung-Box statistics (200.67-240.22) strongly reject the null of no autocorrelation at the 1% level across all lags, indicating persistent serial dependence in NEPSE returns. However, subsample analysis reveals substantial temporal variation. Notably, the 1995-1997 and 1997-1999 periods show markedly weaker test statistics, with insignificant results at higher lags (Lag 5: 9.586, Lag 10: 9.766 for 1997-1999), suggesting brief episodes of improved efficiency. Conversely, the 2003-2007 period exhibits exceptionally strong autocorrelation (statistics exceeding 90-131), coinciding with post-conflict market restructuring. Most recently, the 2024-2025 period demonstrates insignificant autocorrelation at all lags, indicating potential efficiency gains following full digital automation.

The Runs test reveals even stronger evidence of non-randomness, with the full-sample statistic (-18.32***) strongly rejecting randomness. Only three subperiods show insignificant results: 1995-1997 (0.34), 1997-1999 (-0.71), and 2024-2025 (-1.20), aligning precisely with the Ljung-Box efficiency episodes. Variance Ratio statistics are consistently negative across all subperiods and lags, indicating mean-reverting behavior where variance grows sub-linearly with holding period. The sole exceptions—marginal insignificance at k=16 during 1997-1999 and 2024-2025—suggest that predictability concentrates primarily in short-term dynamics.

(Detailed results for the linear tests—specifically the Ljung-Box, Runs, and Variance Ratio tests—are provided in Appendix Table B.1).

Figure 2 corroborates and extends these findings through rolling window analysis with daily overlap, providing smooth visualization of efficiency evolution. Panel (a) reveals the dramatic 1997-1998 efficiency episode identified in Table B.1, with Ljung-Box p-values surging from near-zero to 1.0—indicating complete autocorrelation absence during political instability when limited market participation temporarily eliminated exploitable patterns. Following this brief episode, p-values return to persistently low levels through 2025, confirming that inefficiency re-emerged and persisted despite subsequent digitalization (2018-2021) and increased retail participation.

Panels (b) and (c) show synchronized patterns across Runs and Variance Ratio tests, with all tests identifying the same 1997-1998 efficiency window followed by persistent inefficiency. The consistency across three independent tests—evaluating autocorrelation, randomness, and random walk properties—rules out statistical artifacts and confirms genuine regime changes in market behavior.

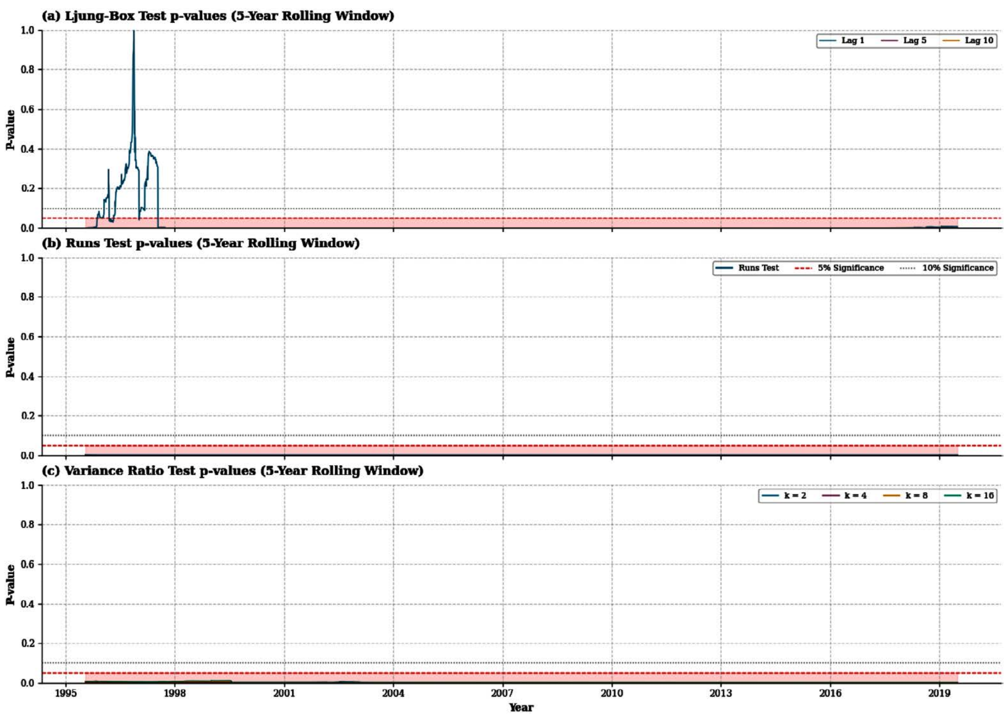


Figure 2: Linear Efficiency Test p-values using 5-Year Rolling Window

5.2.2 Non-Linear Efficiency Diagnostics

To complement the linear efficiency tests, we examine nonlinear dependencies through ARCH-LM, McLeod-Li, and BDS tests applied to pre-whitened returns. These tests assess whether conditional heteroskedasticity and higher-order nonlinear patterns persist after removing linear autocorrelation. Table B.2 presents ARCH-LM and McLeod-Li statistics for 15 two-year subsamples, Table B.3 reports BDS test results across multiple specifications, and Figure 3 illustrates ARCH-LM and McLeod-Li rolling window p-values.

The full-sample ARCH-LM statistics (1130.99-1185.47) and McLeod-Li statistics (1948.07-2808.36) overwhelmingly reject the null hypothesis of no ARCH effects at the 1% level across all lags (5, 10, 15, 20). This indicates pervasive volatility clustering—periods of high volatility tend to follow high volatility, and low follows low—throughout NEPSE's history. Unlike the linear tests which identified brief efficiency episodes, nonlinear dependencies remain consistently strong across all subperiods, with only the recent 2024-2025 period showing marginal insignificance at lower lags for ARCH-LM.

Figure 3 corroborates these findings through rolling window analysis. Both panels reveal p-values persistently near zero throughout the entire 30-year sample, with no visible efficiency episodes comparable to the 1997-1998 window identified in linear tests. The ARCH-LM test (Panel a) shows p-values consistently below 0.05 across all four lags, indicating that volatility clustering survives pre-whitening. The McLeod-Li test (Panel b) exhibits identical patterns, confirming that squared residual autocorrelation—a key signature of GARCH effects—pervades NEPSE returns regardless of market conditions.

BDS test results (Table B.3) provide complementary evidence of complex nonlinear structure beyond ARCH-type volatility clustering. Testing across four epsilon multipliers ($\varepsilon = 0.5\sigma, 1.0\sigma, 1.5\sigma, 2.0\sigma$) and three embedding dimensions ($m = 2, 6, 10$), the full-sample statistics overwhelmingly reject the null hypothesis of independent and identically distributed residuals—ranging from 2.26 ($m=2, \varepsilon=2\sigma$) to 1223.34 ($m=10, \varepsilon=0.5\sigma$), all significant at the 1% level. This universal rejection indicates pervasive higher-order nonlinear dependencies that persist even after removing both linear autocorrelation and ARCH effects.

The test's sensitivity varies systematically with specifications—higher embedding dimensions ($m=10$) and smaller epsilon values ($\varepsilon=0.5\sigma$) generate stronger rejection, indicating that long-range dependencies and fine-scale correlation structures dominate NEPSE's nonlinear patterns. Critically, unlike ARCH-LM tests showing emerging improvements in 2024-2025, BDS statistics remain consistently high even in the most recent period (e.g., $m=10, \varepsilon=0.5\sigma$: 2325.32***), suggesting that while volatility clustering may be moderating, deeper behavioral complexities—herding, feedback trading, regime-dependent risk preferences—persist despite digitalization and regulatory enhancements.

The synchronized rejection across all three tests and all specifications provides compelling evidence that nonlinear inefficiency is more persistent than linear inefficiency in NEPSE. While political crises temporarily eliminated linear autocorrelation (1997-1999), volatility clustering and higher-order dependencies remained unaffected, suggesting that information shocks continue to propagate through variance and complexity channels even when mean return predictability disappears. This pattern aligns with AMH's prediction that different forms of inefficiency adapt at different rates depending on the learning mechanisms required to arbitrage them away—exploiting linear patterns requires simple technical analysis, while eliminating volatility clustering and chaotic dynamics demands sophisticated risk management and institutional development occurring more slowly.

Notably, the 2021-2023 period exhibits particularly strong ARCH effects despite full digital automation, with test statistics exceeding many earlier periods. This counterintuitive result suggests that increased retail participation and heightened market sentiment during the COVID-19 bull market amplified volatility clustering rather than dampening it—consistent with behavioral finance insights that emotional trading exacerbates volatility persistence. Only the most recent 2024-2025 period shows emerging signs of reduced

ARCH effects at lower lags, potentially reflecting maturation of digital infrastructure and improved market stability, though BDS tests confirm that fundamental nonlinear complexity remains embedded in return dynamics.

The persistent nonlinear inefficiency has important implications for risk management and portfolio allocation. Standard volatility models assuming constant variance will systematically misprice securities traded on NEPSE, while GARCH-family models accounting for volatility clustering and regime-switching become essential for accurate risk assessment. The universal rejection across ARCH-LM, McLeod-Li, and BDS tests strongly justify the GARCH and Markov-Switching analyses undertaken in subsequent sections, as these models are specifically designed to capture the multi-dimensional time-varying volatility and nonlinear patterns documented here.

(Detailed results for the non-linear tests—specifically the ARCH-LM and McLeod-Li tests—are provided in Appendix Table B.2, and BDS test in Appendix B.3).

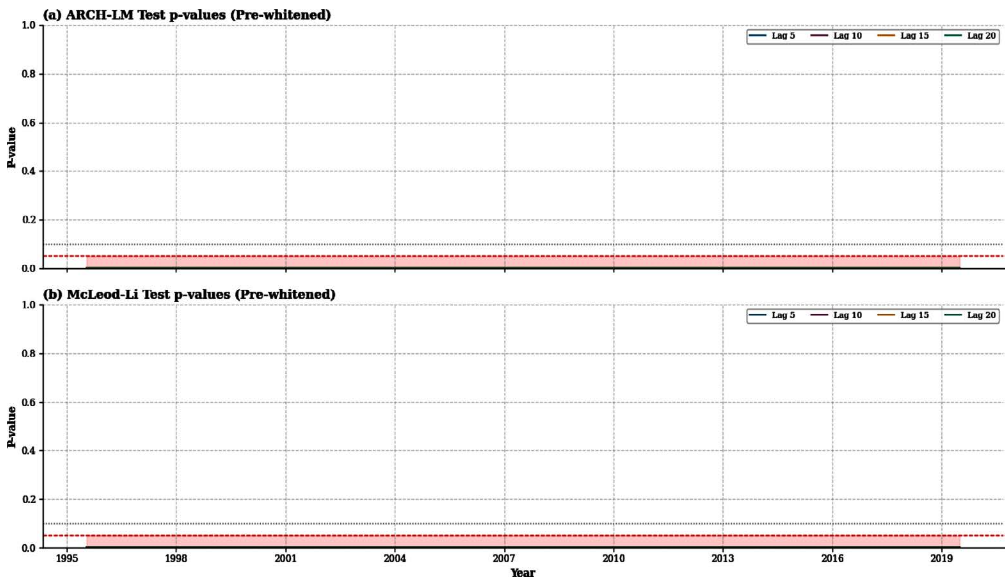


Figure 3: ARCM-LM and McLeod-Li Tests p-values using 5-Year Rolling Window

5.3 GARCH and EGARCH Results

5.3.1 Volatility Persistence and Clustering

Table 3 provides the GARCH (1,1) estimation results for the full sample. The model confirms highly persistent volatility dynamics characteristic of emerging markets. The ARCH coefficient ($\alpha_1 = 0.20$, $p < 0.001$) captures short-run volatility reactions to return shocks, while the GARCH coefficient ($\beta_1 = 0.70$, $p < 0.001$) measures persistence of past volatility. The sum $\alpha_1 + \beta_1 \approx 0.90$), indicates that volatility shocks decay slowly, with approximately 90% of current volatility carrying forward to the next period. This high persistence implies that turbulent periods extend over prolonged intervals before dissipating, a pattern inconsistent with market efficiency where information shocks should be rapidly incorporated into the prices.

Table 3: GARCH (1,1) Model Estimation Results

Parameter	Coefficient	Std. Error	z-Statistic	p-Value	95% Confidence Interval
Mean Model					
M	8.3535×10^{-5}	1.242×10^{-4}	0.673	0.501	$[-1.599 \times 10^{-4}, 3.269 \times 10^{-4}]$
Volatility Model					
Ω	1.4708×10^{-5}	9.556×10^{-13}	1.539×10^{7}	<0.001	$[1.471 \times 10^{-5}, 1.471 \times 10^{-5}]$
α_1	0.2000	0.02169	9.220	<0.001	[0.157, 0.243]
β_1	0.7000	0.02075	33.728	<0.001	[0.659, 0.741]

Figure 4 displays the conditional volatility series σ_t^2 estimated from the GARCH(1,1) model. The plot reveals pronounced volatility clustering across the entire sample, with distinct episodes of heightened uncertainty. Notable volatility spikes occur during 1997-1999 (political crisis), 2007-2009 (global financial crisis), 2015-2016 (earthquake aftermath), 2020-2021 (COVID-19 bull market), and 2022-2023 (monetary tightening). These episodes are followed by extended periods of elevated volatility rather than rapid mean reversion, confirming the persistence captured by the high $\alpha_1 + \beta_1$ sum. Conversely, the 2010-2013 and 2017-2019 periods exhibit sustained low-volatility regimes, demonstrating that NEPSE alternates between distinct volatility states—motivating the Markov-Switching analysis.

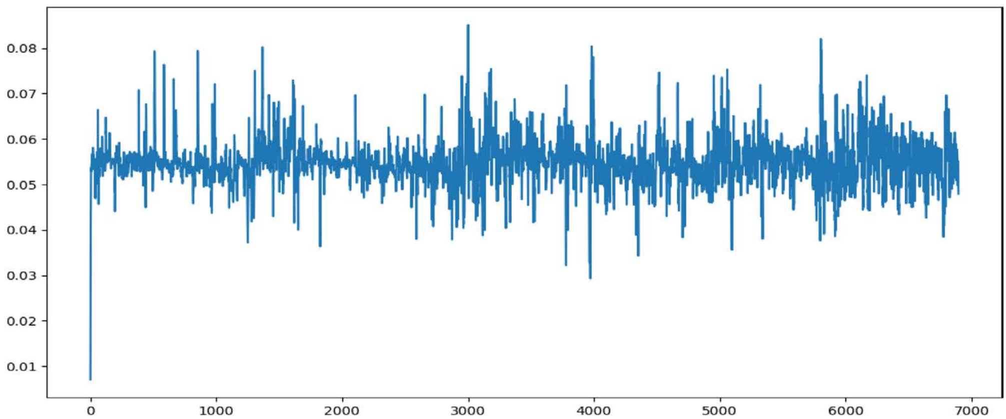


Figure 4: Conditional Volatility from GARCH (1, 1) Model

5.3.2 Asymmetric Volatility Effects

To examine whether negative return shocks generate stronger volatility responses than positive shocks—the "leverage effect" documented in developed markets—we estimate the EGARCH(1,1) specification. Table 4 presents the results.

Table 4: EGARCH Model Estimation Results

Parameter	Coefficient	Std. Error	z-Statistic	p-Value	95% Confidence Interval
Mean Model					
M	-23784×10^{-4}	1.130×10^{-4}	-2.104	0.035	$[-4.594 \times 10^{-4}, -1.630 \times 10^{-5}]$
Volatility Model					
Ω	-1.4692	0.293	-5.007	<0.001	[-2.044, -0.894]
α_1	0.5282	0.04918	10.742	<0.001	[0.432, 0.625]
γ_1	0.0279	0.01791	1.557	0.120	[-0.00722, 0.06299]
β_1	0.8339	0.03316	25.151	<0.001	[0.769, 0.899]

The magnitude coefficient ($\alpha_1 = 0.5282$], $p < 0.001$) and persistence coefficient ($\beta_1 = 0.8339$, $p < 0.001$) remain highly significant, confirming volatility clustering under the exponential specification. Critically, the asymmetry parameter ($\gamma_1 = 0.0279$, $p = 0.12$) is statistically insignificant, indicating no systematic leverage effect in NEPSE returns. Unlike developed markets where negative shocks amplify volatility more than positive shocks of equal magnitude, NEPSE exhibits symmetric volatility responses—both good and bad news produce comparable variance increases. This absence of asymmetry is likely to reflect NEPSE's retail-dominated structure and limited institutional short-selling. In developed markets, leverage effects arise partly from mechanical factors (debt-to-equity ratio increases when stock prices fall) and investor psychology (loss aversion). NEPSE's institutional characteristics— minimal margin trading, limited derivatives markets, and predominantly long-only retail investors—weaken these channels. Additionally, emerging market investors may react emotionally to both positive surprises (fear of missing out) and negative surprises (panic selling), generating symmetric volatility spikes. The symmetric volatility response has practical implications for risk management and options pricing. Standard models assuming leverage effects (like EGARCH with $\gamma < 0$) would misspecify NEPSE volatility dynamics. The simpler GARCH(1,1) specification adequately captures NEPSE's volatility clustering without requiring asymmetry adjustments, supporting its use in subsequent Markov-Switching analysis where regime-dependent variance is modeled symmetrically.

Figure 5 displays the conditional volatility series from the EGARCH model, revealing patterns consistent with the GARCH estimates but with enhanced resolution of extreme episodes. The most prominent feature is the dramatic volatility spike around observation1000 (late 1997-early 1998), coinciding with the Asian financial crisis and domestic political instability, where conditional variance briefly exceeded 12% daily—an exceptionally high level indicating near-panic market conditions. Additional major spikes appear around observations 600-800 (late 1997), 3000 (mid-2007, global financial crisis onset), 4000 (2011-2012), and 6500-7000 (2020-2023, COVID bull market and subsequent correction). The EGARCH specification's logarithmic transformation better captures these extreme volatility episodes without imposing non-negativity constraints on parameters, allowing more flexible modeling of volatility asymmetry. Despite this flexibility, the absence of significant leverage effects ($\gamma_1 \approx 0$) indicates that NEPSE's volatility clustering is driven primarily by persistence mechanisms rather than asymmetric news responses. The symmetric pattern likely reflects NEPSE's retail-dominated structure and limited institutional short-selling—both positive surprises (FOMO-driven buying) and negative surprises (panic selling) generate comparable volatility increases among predominantly long-only, sentiment-driven investors. Comparing Figures 4 and 5, both models identify identical volatility regime periods, but EGARCH assigns higher conditional variance to extreme episodes while maintaining lower baseline volatility during calm periods. This suggests that while asymmetry is absent, allowing for exponential variance dynamics improves the model's ability to distinguish between normal and crisis volatility states—a feature exploited in the Markov-Switching analysis that follows.

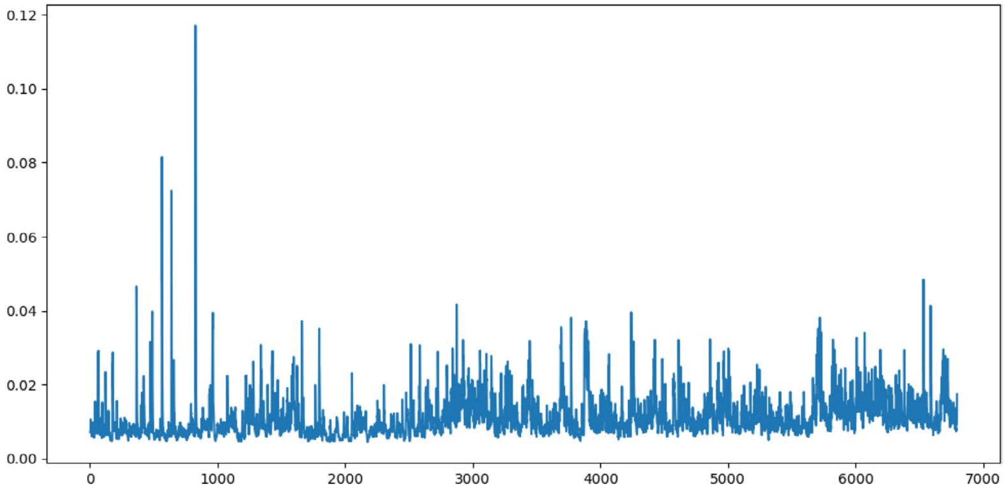


Figure 5: Conditional Volatility of EGARCH Model

The persistent volatility clustering documented by both GARCH and EGARCH models, combined with the absence of leverage effects, provides crucial insights for the subsequent Markov-Switching analysis. The alternation between extended low-volatility and high-volatility regimes visible in both figures—with sharp transitions rather than gradual changes—motivates modeling NEPSE returns as switching between distinct volatility states rather than following a single continuous variance process.

5.4 Markov-Switching Model Results

The Markov-Switching Model identifies two distinct volatility regimes characterizing in the NEPSE index: regime 0 (low volatility) and regime 1 (high volatility). The persistence of each regime is assessed using the expected regime duration (in trading days), calculated from the estimated transition probabilities.

The Markov-Switching model identifies two distinct volatility regimes characterizing NEPSE dynamics: Regime 0 (low volatility/calm) and Regime 1 (high volatility/turbulent). Table 5 presents parameter estimates and transition probabilities.

Table 5: Estimation Results of the Markov-Switching Model

Parameter	Coefficient	Std. Error	z-Statistic	p-Value	95% Confidence Interval
Regime 0					
Constant	-1.445×10^{-5}	9.55×10^{-5}	-0.151	0.880	[-0.0001, 0.0001]
σ^2	2.519×10^{-5}	9.75×10^{-7}	25.830	<.001	[2.23×10^{-5}, 2.71×10^{-5}]
Regime 1					
Constant	0.0010	0.0000	2.755	0.006	[0.0000, 0.0020]
σ^2	0.0003	1.22×10^{-5}	28.258	0.000	[0.000, 0.000]
Transition Probabilities					
P_{00}	0.9347	0.005	172.626	0.000	[0.924, 0.945]
P_{10}	0.1060	0.009	11.307	0.000	[0.088, 0.124]

5.4.1 Regime Characteristics and Persistence

The estimated regime-specific parameters reveal substantial heterogeneity in return distributions. Regime 0 exhibits near-zero mean returns ($\mu_0 = -1.45\times10^{-5}$, $p = 0.880$) with low conditional variance ($\sigma_0^2 = 2.52\times10^{-5}$, equivalent to 0.50% daily volatility), characterizing periods of market stability and subdued trading activity. In contrast, Regime 1 displays modestly positive mean returns ($\mu_1 = 0.001$, $p = 0.006$) accompanied by substantially elevated variance ($\sigma_1^2 = 0.0003$, equivalent to 1.73% daily volatility)—approximately 12 times higher than Regime 0. The positive mean in high-volatility periods suggests that turbulence in NEPSE often coincides with speculative rallies and heightened trading volumes rather than pure downside risk, consistent with retail-driven momentum behavior documented in emerging markets.

The transition probabilities reveal asymmetric regime persistence. The probability of remaining in Regime 0 ($P_{00} = 0.9347$) substantially exceeds the probability of remaining in Regime 1 ($P_{11} = 1 - P_{10} = 0.8940$), implying that calm periods are more durable than turbulent episodes.

Translating these probabilities into expected regime durations yields:

Regime 0 (low volatility)

$$D_0 = \frac{1}{1-P_{00}} = \frac{1}{1\text{-}0.9347} = \frac{1}{0.0653} \approx 15.32 \textit{ trading days.} \tag{8}$$

Regime 1 (high volatility):

$$D_1 = \frac{1}{1-P_{11}} = \frac{1}{1\text{-}0.8940} = \frac{1}{0.1060} \approx 9.43 \textit{ trading days.} \tag{9}$$

These durations indicate that while both regimes exhibit meaningful persistence—measured in weeks rather than days—market turbulence is inherently more transient, with volatility shocks typically dissipating within two weeks absent sustained fundamental deterioration.

Figure 6 displays the smoothed regime probabilities—the model's posterior assessment of which state governed NEPSE returns at each point in the sample. When the Regime 1 probability (blue line) approaches unity, the market was almost certainly experiencing high-volatility conditions; conversely, probabilities near zero indicate definitive Regime 0 (calm) periods.

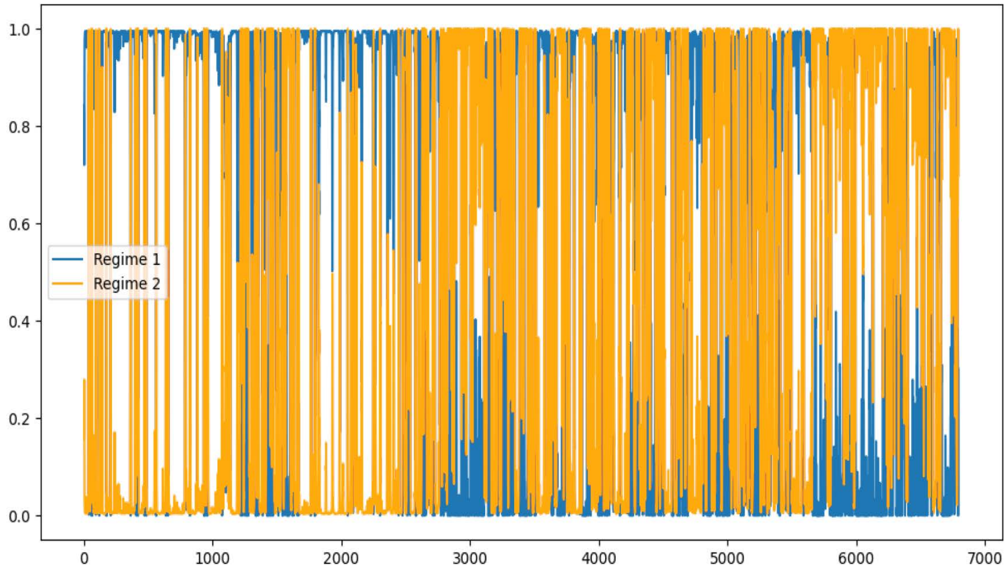


Figure 6: Smoothed Regime Probabilities from Markov-Switching Model

The regime classification reveals distinct volatility episodes aligned with identifiable economic and political events. Prolonged Regime 1 periods occur during 1997-1999 (Asian financial crisis and Maoist insurgency escalation), 2007-2009 (global financial crisis), 2015-2016 (earthquake and India trade blockade), 2020-2021 (COVID-19 pandemic and subsequent bull market), and 2022-2023 (monetary tightening and correction).

Notably, the model classifies the entire 2020-2021 bull market as high-volatility despite strongly positive returns, confirming that Regime 1 captures uncertainty and rapid price changes rather than directional risk alone. The frequent regime transitions visible in Figure 6—alternating between multi-week blocks of stability and turbulence—visually reinforce the calculated persistence metrics and demonstrate that NEPSE volatility evolves through discrete state changes rather than continuous mean reversion.

The regime-switching behavior provides strong AMH support by demonstrating that market conditions evolve adaptively rather than remaining constant. Efficiency likely varies across regimes—Regime 0 periods may permit gradual information processing and tighter arbitrage, while Regime 1 turbulence disrupts normal price discovery mechanisms as emotional trading and liquidity constraints dominate. The asymmetric persistence (longer calm periods, shorter turbulent episodes) suggests that NEPSE possesses inherent stabilizing mechanisms that eventually restore order following shocks, consistent with adaptive investor learning and institutional responses to crisis conditions. However, the repeated regime switches over 30 years—without converging toward permanent efficiency—indicate that adaptation is cyclical rather than progressive, aligning with AMH's prediction of time-varying rather than monotonically improving efficiency.

5.5 Discussion and Implications

5.5.1 Discussions

Comprehensive efficiency diagnostics demonstrate that NEPSE exhibits evolutionary rather than static efficiency characteristics, providing strong empirical support for Lo's (2004, 2005) AMH framework. Unlike traditional weak-form EMH rejections concluding permanent inefficiency, our findings reveal adaptive efficiency—markets shifting between inefficiency and brief efficient episodes in response to changing institutional conditions and competitive intensity.

The 1997-1999 efficiency episode, where multiple tests simultaneously failed to reject efficiency, coincided with severe political instability and sharply reduced trading volumes. This paradoxically eliminated exploitable patterns by reducing market participation below the threshold necessary for systematic arbitrage. Once normal trading resumed post-1999, inefficiency re-emerged through 2023, demonstrating that efficiency depends critically on competitive intensity rather than information availability alone. This challenges the conventional view that market development monotonically improves efficiency; instead, efficiency "waxes and wanes" (Lo, 2004) with active competitors and profit opportunities.

These temporal patterns extend prior NEPSE studies (Dangol, 2012; Jha & Dhungana, 2021; Joshi, 2024) that documented static inefficiency by revealing underlying cyclical variation. Internationally, Hiremath and Kumari (2014) and Khuntia and Pattanaik (2018) document similar adaptive patterns in India and China following macroeconomic reforms. Critically, Rönkkö et al. (2024) demonstrate that small market size does not predetermine inefficiency—structural reforms progressively improve efficiency even in small Finnish markets, supporting our finding that NEPSE's digitalization drives observable 2024-2025 gains rather than market scale alone.

The time-varying efficiency pattern has direct consequences—trading strategies effective during inefficient periods (momentum, mean-reversion) would fail during efficiency episodes, generating losses for investors assuming constant patterns. This underscores that strategy performance is regime-dependent, requiring continuous adaptation. For long-term investors, cyclical efficiency suggests that while temporary arbitrage opportunities exist, competitive forces eventually eliminate exploitable patterns, potentially favoring passive indexing over extended horizons.

GARCH(1,1) estimation confirms highly persistent volatility ($\alpha_1 + \beta_1 = 0.90$), indicating slow shock dissipation characteristic of emerging markets. Shahid et al. (2019) report similar persistence (0.88) in Pakistan, demonstrating regional consistency suggesting common mechanisms—limited liquidity, retail-dominated trading, behavioral herding—rather than country-specific factors drive volatility dynamics.

High persistence creates critical risk management implications. Standard models assuming quick variance stabilization systematically underestimate NEPSE risk exposure, potentially leading to inadequate hedging. For policymakers, persistent volatility complicates stabilization—circuit breakers must account for extended turbulence duration rather than expecting quick normalization.

The EGARCH specification reveals no significant asymmetry ($\gamma_1 = 0.028$, $p = 0.120$), contrasting developed markets where negative shocks amplify volatility more than positive shocks. This symmetric response reflects NEPSE's institutional characteristics: retail-dominated structure, minimal margin trading, limited derivatives, and predominantly long-only investors. Both positive surprises (fear-of-missing-out buying) and negative surprises (panic selling) generate comparable volatility among sentiment-driven retail traders. Cruz-Hernández and Mora-Valencia (2024) document similar patterns in Latin America, suggesting institutional structure—not investor sophistication alone—determines asymmetrical presence. Symmetric volatility simplifies risk management—investors face comparable variance increases from both good and bad news, unlike developed markets requiring asymmetric hedging. Standard GARCH specifications adequately capture NEPSE dynamics without asymmetry adjustments, reducing model complexity.

Markov-Switching results reveal asymmetric regime persistence—calm periods average 15.32 days while turbulent episodes last 9.43 days. This shorter high-volatility duration indicates increasing institutional resilience: markets experience frequent disruptions but revert quickly once uncertainty subsides. Okorie and Lin (2021) show COVID-19 produced heterogeneous responses—India experienced sustained efficiency decline while Russia improved—suggesting institutional resilience, not shock magnitude, determines recovery speed. NEPSE's quick turbulence resolution suggests effective crisis management despite limited development.

Critically, efficiency varies across volatility states—high-volatility regimes exhibit stronger autocorrelation and nonlinear dependence while calm periods approach efficiency. This aligns with Munir et al.'s (2022) South Asian evidence that contrarian strategy profitability varies with market conditions. Investment should employ regime-conditional strategies rather than assuming constant patterns. During turbulent periods, exploiting anomalies may generate abnormal returns; during calm regimes, competitive arbitrage eliminates patterns, favoring passive approaches.

The regime-dependent pattern supports Noreen et al.'s (2022) finding that efficiency varies with investor behavioral adaptations—myopic loss aversion generates episodic inefficiencies during stress even as informational efficiency improves. NEPSE's coexistence of efficiency gains (reduced nonlinear dependence 2024-2025) and sustained volatility clustering demonstrates adaptive evolution proceeds unevenly across dimensions—informational processing enhances while behavioral volatility responses persist, consistent with AMH's gradual competitive adaptation prediction.

The 2024-2025 period shows unprecedented efficiency gains—Ljung-Box, Runs, and Variance Ratio tests fail to reject efficiency for the first time since 1997-1999. Unlike the earlier episode driven by limited participation, recent improvement coincides with technological transformation documented by Vaidya (2021): full digital trading platform, automated settlement, improved SEBON regulatory oversight, no. of DEMAT account increasing & rising investor participation, and institutions' financial literacy initiatives.

This mirrors adaptive improvements in other emerging markets. Xiong et al. (2019) document progressive efficiency gains in China following regulatory reforms. However, persistence of volatility clustering ($\alpha_1 = 0.5282$ in EGARCH) during efficiency improvements indicates that while information processing enhanced, behavioral uncertainty responses remain—consistent with AMH's multi-dimensional adaptation view.

Cruz-Hernández and Mora-Valencia (2024) document similar Latin American patterns—calendar anomalies dissipate while volatility persistence remains elevated, demonstrating informational efficiency and volatility dynamics adapt independently.

NEPSE exhibits identical evolution; linear return predictability weakens (informational efficiency improves) while ARCH effects persist (behavioral clustering continues). This finding reveals that technological advancement alone does not eliminate all inefficiencies; behavioral frictions require investor learning and institutional maturation, processes occurring at different speeds than information infrastructure improvements.

5.5.2 Policy and Investment Implications

For Regulators: Policymakers should implement (1) regime-calibrated surveillance intensifying when markets enter high-volatility states, (2) continued digitalization given 2024-2025 efficiency gains validating recent reforms, (3) volatility-aware circuit breakers accounting for high persistence ($\alpha + \beta = 0.90$), and (4) liquidity-enhancing programs reducing volatility clustering through improved price discovery.

For Investors: (1) Employ regime-conditional strategies adapting to current volatility state rather than assuming constant patterns, (2) use GARCH-based risk forecasts given persistence underestimation by standard models, and (3) maintain long-horizon perspective recognizing mean-reverting regime transitions support buy-and-hold strategies, though recent efficiency improvements suggest historical anomalies may weaken.

Research Extensions: Future work should (1) incorporate macroeconomic variables isolating intrinsic persistence from exogenous shocks, (2) test sectoral heterogeneity revealing whether efficiency varies by information environment, (3) construct behavioral proxies assessing whether regime transitions reflect adaptive learning versus persistent biases, and (4) systematically compare with neighboring markets clarifying regional versus country-specific efficiency drivers.

Overall, findings support the view that NEPSE exhibits evolving adaptive efficiency characterized by improving informational processing alongside persistent behavioral and structural frictions—a pattern consistent with AMH's core prediction that efficiency emerges through gradual competitive adaptation rather than instantaneous rational adjustment.

Conclusion

This study provides the first comprehensive empirical test of the AMH in Nepal Stock Exchange using nearly three decades of daily data (July 1995-February 2025). Employing subsample and rolling window efficiency diagnostics, GARCH-family volatility models, and Markov-Switching regime analysis, the study demonstrates that NEPSE exhibits time-varying efficiency, persistent volatility clustering, and regime-dependent dynamics—patterns fundamentally inconsistent with traditional EMH but strongly supporting Lo's (2004, 2005) AMH framework.

The combined evidence from linear and nonlinear efficiency tests reveals systematic temporal variation. Distinct efficiency episodes—1997-1999 during political crisis with limited participation, and emerging signals in 2024-2025 following digital automation documented by Vaidya (2021)—interspersed with prolonged inefficiency (1999-2023) directly contradict both permanent efficiency and permanent inefficiency assumptions. Instead, efficient "waxes and wanes" with competitive forces and institutional conditions, precisely as AMH predicts. These findings provide strong statistical grounds to reject the null hypothesis (H_0) that NEPSE returns follow a random walk with constant efficiency, supporting the alternative hypothesis (H_1) adaptive, context-dependent efficiency.

GARCH (1,1) and EGARCH estimations confirm highly persistent volatility ($\alpha_1 + \beta_1 = 0.90$), characteristic of emerging markets where shocks dissipate slowly. The absence of leverage effects ($\gamma_1 = 0.028$, $p = 0.120$) distinguishes NEPSE from developed markets—both positive and negative shocks generate symmetric volatility increases, reflecting retail-dominated structure rather than institutional leverage mechanisms. Markov-Switching analysis identifies two distinct regimes: low-volatility states persisting 15.32 trading days and high-volatility episodes lasting 9.43 days. The shorter turbulent duration indicates increasing institutional resilience, with markets recovering relatively quickly from shocks.

This study extends prior NEPSE research (Dangol, 2012; Jha & Dhungana, 2021; Joshi, 2024) by documenting not merely weak-form inefficiency but its cyclical evolution across three technological phases (manual 1995-2007, hybrid 2007-2021, digital 2021-2025). The progressive reduction in nonlinear dependence during 2021-2025, coupled with shorter turbulent regimes, suggests gradual resilience improvement attributable to digital trading implementation, regulatory enhancements, and increased retail participation. However, persistent volatility clustering (EGARCH) indicates that while information processing has enhanced, behavioral frictions remain—demonstrating multi-dimensional adaptation where informational efficiency improves while volatility responses persist, consistent with AMH's prediction that efficiency evolves unevenly across market dimensions.

Future research could incorporate macroeconomic variables isolating intrinsic persistence from exogenous shocks, conduct sectoral analysis revealing efficiency variation by information environment, employ high-frequency data for microstructure analysis, systematically comparing with neighboring markets, and construct behavioral proxies testing whether regime transitions reflect adaptive learning versus persistent biases.

The fundamental insight is that NEPSE efficiency is neither permanent nor absent but adaptive evolving with competitive forces, institutional development, and technology advancement. Market development is nonlinear; efficiency improvements require not only technological infrastructure but also investor learning and institutional maturation occurring at different rates. This understanding has important implications for emerging market policy design, emphasizing sustainable structural reforms rather than expecting automatic convergence to developed market standards.

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Appendix A:

Mathematical Equations of Preliminary Tests

1. Augmented Dickey-Fuller (ADF) test

With trend

$$\Delta y_t = c + bt + \delta y_{t-1} - \Sigma_{j=2}^{p} \beta_j \Delta y_{t-j+1} + u_t$$

With constant only

$$\Delta y_t = c + \delta y_{t-1} - \Sigma_{j=2}^{p} \beta_j \Delta y_{t-j+1} + u_t$$

Here, Δy_t is the first differences of the series, y_{t-1} is the lagged level, β_j are the coefficients ofqlagged differences, and u_t represents the error term.

2. Phillips-Person (PP) test

With trend

$$\Delta y_t = c + bt + \delta y_{t-1} - \varnothing y_{t-1} + u_t$$

With constant only

$$\Delta y_t = c + \delta y_{t-1} - \varnothing y_{t-1} + u_t$$

3. Kwiatkowski – Phillips – Schmidt – Shin (KPSS) test

$$(1)\ \Delta y_t = x'_t\, \delta + u_t$$

where x'_t represents the exogenous variables, and u_t represents the error term.

4. Ljung-Box test

$$LB\,(q) \quad \sim\partial \quad X^2\,(q),$$

$$= n\, \Sigma_{s=1}^{q} \frac{n+2}{n-1}\, p\,(s)^2,$$

$$p(s) = \frac{Cov\,(R_t,\, R_{t-s})}{Vat\,(R_t)}$$

where the chi-squared distribution is denoted by $X\text{^}2(q)$ having degrees of freedom (q) and no. of observations (n). Here, $Cov\,(R_t\,,\, R_{t-s})$ denotes returns' autocovariance at different lag (s), and $Var\,(R_t\,)$ and denotes returns' variance.

5. Run test

$$Z = \frac{R - \mu_R}{\sigma_R} \approx N(0,\, 1)$$

$$where,\ \mu_R = \frac{2n_0n_1}{n} + 1,\ and\ \sigma_R = \sqrt{\frac{2n_0n_1 - (2n_0n_1 - n)}{n^2(n-1)}}$$

6. Variance Ratio test:

$$VR(K) = 1 + 2\sum_{s-1}^{k-1} \frac{k-s}{k} p\ (s)$$
$$= \frac{1}{k} \frac{Var(R_t + \sum_{s-1}^{k-1} \frac{k-s}{k} R_{t-s})}{Var(R_t)} \quad = \frac{1}{k} \frac{Var(P_t - P_{t-k})}{Var(P_t - P_{t-1})}$$

where $VR\ (K)$, R_t, and P_t denote the variance ratio for holding period k, the return at time t, and the price at time t, respectively. k and ρ(s) are the holding period (no. of lags) and the s-th order autocorrelation coefficient of the returns, respectively.

7. ARCH-LM test

$$e_t^2 = a_0 + \sum_{s=1}^{q} a_s\, e_{t-s}^2 + V_t,$$
$$(n\text{-}q).R^2 \quad a \approx \quad X^2(q)$$

where 'e' denotes the residuals obtained from the pre-whitening AR model, 'q' is the highest order lag, 'a' is the model fitting parameters, 'vt' is the white noise process, and 'R2' is the coefficient of determination.

8. McLeod -Li test

$$Q(m) = \frac{n(n+2)}{n\text{-}k} \sum_{k=1}^{m} r_a^2(k)$$

where n denotes the sample size, k denotes the number of parameters (for AR (1), m denotes the number of lags, $r_a\ (k)$ denotes the autocorrelation of squared residuals at lag k, and $\sum_{k=1}^{m} r_a^2(k)$ denotes the sum of squared autocorrelations up to lag m.

9. Brock-Dechert-Scheinkman (BDS) Test

$$W_{m,\,n}\ (\epsilon) = \sqrt{n}\ \frac{T_{m,n}\ (\epsilon)}{V_{m,n}\ (\epsilon)}$$

where $W\_(m,n)\ (\epsilon)$, n, m, and (ϵ) denote BDS statistics, sample size, the embedding dimension, and the metric bound, the maximum difference between pairs of observations counted in computing the correlation integral.

Appendix B:

Results of Preliminary Tests for Market Efficiency

Table B.1: Ljung–Box, Run, and Variance Ratio Test Results

	Ljung-Box Test Statistic						Run Test Statistic		Variance Test Statistic							
Period	Lag 1	I/E	Lag 5	I/E	Lag 10	I/E		I/E	k = 2	I/E	k = 4	I/E	k = 8	I/E	k = 16	I/E
Total	200.6695***	I	213.3037***	I	240.2202***	I	-18.3208***	I	-13.1685***	I	-13.3258***	I	-11.5418***	I	-9.6844***	I
1995-07/1997-06	4.0203**	I	9.586	E	14.641	E	0.343	E	-4.0711***	I	-3.4626***	I	-3.2389***	I	-2.9188***	I
1997-07/1999-06	4.195**	I	6.299	E	9.766	E	-0.714	E	-2.6288***	I	-2.227**	I	-2.0097**	I	-1.922	E
1999-07/2001-06	0.283	E	127.2946***	I	134.3291***	I	-6.6529***	I	-3.2341***	I	-2.0077**	I	-1.561	E	-1.405	E
2001-07/2003-06	17.3641***	I	22.2866***	I	27.7525***	I	-7.1749***	I	-3.7703***	I	-3.4261***	I	-3.0679***	I	-2.6221***	I
2003-07/2005-06	46.8347***	I	54.4582***	I	58.0121***	I	-6.2866***	I	-3.0889***	I	-3.3271***	I	-3.1986***	I	-2.9353***	I
2005-07/2007-06	90.422***	I	108.1182***	I	131.5163***	I	-8.0884***	I	-1.527	E	-3.2555***	I	-3.6723***	I	-3.2634***	I
2007-07/2009-06	54.5793***	I	59.1976***	I	66.2107***	I	-6.8144***	I	-3.3597***	I	-5.2273***	I	-4.8744***	I	-4.0595***	I
2009-07/2011-06	25.7464***	I	27.3266***	I	33.1193***	I	-6.8762***	I	-4.1443***	I	-4.2242***	I	-3.7563***	I	-3.0109***	I
2011-07/2013-06	19.9718***	I	36.6174***	I	111.9837***	I	-4.2546***	I	-3.1417***	I	-4.4086***	I	-3.5517***	I	-2.5758**	I
2013-07/2015-06	38.4404***	I	39.2832***	I	46.7248***	I	-4.2838***	I	-3.021***	I	-3.8626***	I	-3.6392***	I	-2.877***	I
2015-07/2017-06	24.6165***	I	26.7295***	I	34.4132***	I	-6.0687***	I	-4.1601***	I	-4.5718***	I	-4.0125***	I	-3.3778***	I
2017-07/2019-06	10.9157***	I	11.6229**	I	14.395	E	-3.4901***	I	-5.521***	I	-5.6466***	I	-4.8111***	I	-3.8172***	I
2019-07/2021-06	1.811	E	11.6024**	I	14.078	E	-2.0249**	I	-4.1737***	I	-4.219***	I	-3.3612***	I	-2.68***	I
2021-07/2023-06	5.0706**	I	12.931**	I	24.693***	I	-2.9759***	I	-5.9008***	I	-6.5593***	I	-5.3015***	I	-4.1277***	I
2024-07/2025-02	0.242	E	6.204	E	15.048	E	-1.199	E	-3.5031***	I	-3.1067***	I	-2.5649**	I	-1.920	E

Note: Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively. E denote market efficiency and I denote market inefficiency.

Table B.2: ARCH-LM and McLeod-Li Test Result

	ARCH-LM Test Statistic								McLeod-Li Test Statistic							
Period	Lag 5	I/E	Lag 10	I/E	Lag 15	I/E	Lag 20	I/E	Lag 5	I/E	Lag 10	I/E	Lag 15	I/E	Lag 20	I/E
Total	1130.9871***	I	1158.6005***	I	1180.4807***	I	1185.4711***	I	1948.0715***	I	2306.7113***	I	2668.2225***	I	2808.3589***	I
1995-07/1997-06	28.3456***	I	34.4913***	I	34.7860***	I	35.0471**	I	32.2811***	I	36.6803***	I	37.6769***	I	39.0693***	I
1997-07/1999-06	38.1268***	I	39.3985***	I	24.6569*	E	26.212	E	38.1820***	I	38.8756***	I	39.2084***	I	40.0392***	I
1999-07/2001-06	185.3392***	I	185.6430***	I	186.0000***	I	56.7104***	I	363.6822***	I	365.0042***	I	367.2836***	I	369.0884***	I
2001-07/2003-06	96.4053***	I	95.7104***	I	89.5112***	I	90.7451***	I	157.3424***	I	165.4034***	I	169.8206***	I	171.6673***	I
2003-07/2005-06	31.6542***	I	32.3138***	I	32.5821***	I	32.4645**	I	34.0497***	I	35.0007***	I	35.7401***	I	36.2585**	I
2005-07/2007-06	19.8732***	I	22.2230**	I	25.6962**	I	27.176	E	26.5484***	I	28.7819***	I	31.5762***	I	33.9182**	I
2007-07/2009-06	25.1498***	I	28.1760***	I	28.7163**	I	33.1022**	I	30.4339***	I	33.7309***	I	34.8027***	I	38.2183***	I
2009-07/2011-06	94.0411***	I	110.9280***	I	113.6688***	I	125.5869***	I	164.9192***	I	190.4221***	I	197.9572***	I	199.0780***	I
2011-07/2013-06	173.3939***	I	183.1441***	I	186.2969***	I	190.9771***	I	442.9347***	I	769.7557***	I	957.7652***	I	1108.0571***	I
2013-07/2015-06	52.0731***	I	69.4542***	I	70.5655***	I	79.5357***	I	66.1616***	I	116.1119***	I	117.5542***	I	124.1073***	I
2015-07/2017-06	60.7129***	I	61.2990***	I	59.9898***	I	61.4816***	I	90.3622***	I	93.7993***	I	95.4143***	I	96.2001***	I
2017-07/2019-06	40.1898***	I	47.7865***	I	54.9725***	I	63.5681***	I	46.9285***	I	65.3818***	I	77.4951***	I	96.1563***	I
2019-07/2021-06	96.6701***	I	106.0976***	I	128.3263***	I	126.9680***	I	168.1021***	I	217.7467***	I	341.1215***	I	356.7563***	I
2021-07/2023-06	12.0727**	I	15.633	E	18.323	E	18.966	E	14.7053**	I	21.6253**	I	27.5338**	I	28.5791*	E
2024-07/2025-02	7.188	E	11.662	E	17.473	E	24.705	E	9.9851*	E	20.3651**	I	38.6597***	I	49.2316***	I

Note: Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively. E denote volatility-efficiency and I denote volatility-inefficiency.

Table B.3: Full BDS Test Results for Different Embedding Dimensions (m) and Distance Parameters (ε)

Period	ε = 0.5σ						ε = 1σ						ε = 1.5σ						ε = 2σ					
	m = 2	I/E	m = 6	I/E	m = 10	I/E	m = 2	I/E	m = 6	I/E	m = 10	I/E	m = 2	I/E	m = 6	I/E	m = 10	I/E	m = 2	I/E	m = 6	I/E	m = 10	I/E
Total	4.0027***	I	97.7195***	I	1223.3395***	I	4.0841***	I	54.0226***	I	223.8826***	I	3.0955***	I	32.4681***	I	92.7359***	I	2.2617**	I	20.9608***	I	51.0953***	I
1995-07/1997-06	0.526	E	4.7594***	I	35.9551***	I	0.654	E	4.8919***	I	11.1237***	I	0.673	E	5.0367***	I	10.6793***	I	0.494	E	3.9172***	I	7.9484***	I
1997-07/1999-06	0.830	E	7.6817***	I	27.6070***	I	0.816	E	5.9438***	I	13.4602***	I	0.720	E	5.3878***	I	11.2036***	I	0.572	E	4.3440***	I	9.0298***	I
1999-07/2001-06	1.273	E	23.7615***	I	255.0484***	I	1.332	E	13.0801***	I	42.7504***	I	1.21	E	9.3347***	I	23.4435***	I	1.059	E	7.1368***	I	15.5382***	I
2001-07/2003-06	1.240	E	23.2784***	I	180.3947***	I	1.446	E	15.6936***	I	57.0365***	I	1.225	E	11.3778***	I	30.9951***	I	0.813	E	7.5435***	I	18.5391***	I
2003-07/2005-06	0.628	E	13.9357***	I	182.0351***	I	0.537	E	7.0250***	I	23.4459***	I	0.440	E	4.1477***	I	9.9634***	I	0.423	E	2.9105***	I	5.8065***	I
2005-07/2007-06	0.783	E	17.1771***	I	176.8749***	I	0.831	E	10.6653***	I	39.9190***	I	0.554	E	5.7076***	I	14.2181***	I	0.347	E	4.2506***	I	9.4609***	I
2007-07/2009-06	0.618	E	17.4576***	I	734.1588***	I	0.708	E	9.0382***	I	34.6369***	I	0.547	E	5.2758***	I	12.7132***	I	0.412	E	3.2767***	I	6.4650***	I
2009-07/2011-06	0.744	E	13.3078***	I	199.7984***	I	0.841	E	8.5637***	I	31.1482***	I	0.760	E	6.3969***	I	16.6285***	I	0.658	E	5.2933***	I	12.6795***	I
2011-07/2013-06	1.367	E	27.0838***	I	316.8061***	I	1.404	E	15.6146***	I	49.9637***	I	1.261	E	11.3446***	I	28.6924***	I	1.226	E	10.5175***	I	25.2331***	I
2013-07/2015-06	0.444	E	13.6540***	I	485.3775***	I	0.558	E	8.3916***	I	29.0968***	I	0.572	E	6.5225***	I	17.5487***	I	0.456	E	4.2491***	I	10.1421***	I
2015-07/2017-06	0.766	E	15.5936***	I	447.0186***	I	0.883	E	11.0502***	I	43.5556***	I	0.719	E	7.9162***	I	22.0474***	I	0.535	E	5.2566***	I	11.9621***	I
2017-07/2019-06	0.411	E	12.7249***	I	751.5093***	I	0.489	E	5.5832***	I	19.7762***	I	0.384	E	3.9753***	I	10.9675***	I	0.235	E	2.4065**	I	5.7384***	I
2019-07/2021-06	0.650	E	18.1371***	I	409.4266***	I	0.702	E	11.8825***	I	50.2710***	I	0.568	E	8.0462***	I	24.3517***	I	0.442	E	5.7024***	I	14.5578***	I
2021-07/2023-06	0.220	E	12.1522***	I	1194.4633***	I	0.224	E	4.1703***	I	20.4577***	I	0.104	E	2.1018**	I	7.2721***	I	0.050	E	1.160	E	3.3628***	I
2024-07/2025-02	0.114	E	19.2395***	I	2325.3158***	I	0.160	E	4.3807***	I	27.2627***	I	0.107	E	2.7835***	I	10.5346***	I	0.071	E	1.306	E	4.2779***	I

Note: Statistical significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively. E denote market efficiency and I denote market inefficiency.