An Empirical Assessment of Financial Market Efficiency: Linear and Nonlinear Evidence from the Hang Seng Index (2015–2024)

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ARTICLE INFORMATION

Original Research Paper
Received: 28/12/2025
Accepted: 13/01/2026.
Published: 21/03/2026

Keywords:
Keyword.1:Hang Seng Index
Keyword.2:Weak-form efficiency
Keyword.3:BDS test
Keyword.4:Variance-ratio test
Keyword.5:Volatility clustering

JEL Classification Codes:
G14, G15, C22

Abstract :

This study investigates the weak-form efficiency of the Hong Kong Stock Exchange (HSI) from 2015 to 2024 using 2,464 daily log-returns. By employing a comprehensive battery of linear and nonlinear diagnostics-including BDS and heteroskedasticity-robust variance-ratio tests-the research reveals a complex, mixed efficiency profile. While linear diagnostics suggest near-efficiency and sign randomness, the BDS test and significant multi-day mean reversion expose deep nonlinear dependencies. These findings imply that structural market patterns persist despite apparent randomness. Consequently, while transaction costs may limit immediate arbitrage, the results advocate for enhanced market transparency and the adoption of sophisticated nonlinear risk management models.

Mots clés:
Mot clé.1:Indice Hang Seng
Mot clé.2:Efficience au sensfaible
Mot clé.3:Test BDS
Mot clé.4:Test de rapport de variance
Mot clé.5:Regroupement de la volatilité

Codes de classification JEL :
G14, G15, C22

Résumé :

Cette étude analyse l'efficience de forme faible de la bourse de Hong Kong (HSI) entre 2015 et 2024 via 2 464 rendements logarithmiques. En déployant une batterie complète de diagnostics linéaires et non linéaires-incluant le test BDS et les ratios de variance robustes-la recherche révèle un profil d'efficience mixte et complexe. Si les tests linéaires suggèrent une efficience relative, le test BDS et une réversion à la moyenne significative exposent des dépendances non linéaires profondes. Ces résultats impliquent que des schémas structurels persistent malgré un caractère aléatoire apparent. Bien que les coûts de transaction limitent l'arbitrage, les conclusions préconisent une transparence accrue et l'adoption de modèles de gestion des risques non linéaires sophistiqués.

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1. The introduction:

The Efficient Market Hypothesis (EMH) posits that asset prices fully and instantaneously reflect available information, rendering systematic excess returns unattainable once risk and transaction costs are considered (Fama, 1970, 1991). In its weak form, the EMH implies that returns follow a martingale difference sequence. However, theoretical context requires deeper analysis of return drivers; for instance, Gharbi and Bedrouni (2020) investigated the determinants of stock returns using Arbitrage Pricing Theory, while Marfia (2022) highlighted the distinction between speculation and gambling as drivers of price fluctuations.

Recent literature continues to debate the empirical validity of weak form efficiency, especially in Asian and emerging markets. Studies on Asia Pacific indices suggest that many markets display only partial efficiency (Misiran & Phewchean, 2020; Capital Market Efficiency in Asia, 2022). While earlier work on Hong Kong documents conflicting evidence, comparative studies in other developing markets reinforce these findings of inefficiency. For example, Kennouche (2020) analyzed the Algerian Stock Exchange and found significant inefficiencies, mirroring trends seen in some Asian indices. Additionally, the management of risk in these volatile environments is critical, as Tahi et al. (2021) emphasized using non-parametric approaches like VaR and CVaR. Furthermore, Tomo (2022) argued that structural financial reforms are often necessary to enhance market development and efficiency.

The COVID-19 period and subsequent episodes of geopolitical and macro-financial uncertainty further motivate a reassessment of price efficiency. The literature increasingly employs nonlinear diagnostics—such as the BDS test—to capture complex dependence structures in returns (Zhang & Wang, 2024; López de Lacalle & Orbe, 2023). This shift towards advanced modeling is evident in recent scholarship; Kalafate and Khiari (2023) demonstrated the utility of GARCH models in capturing volatility in commodity markets, while Mansouri and Souilhi (2020) applied EGARCH models to model volatility shocks in speculative assets like Bitcoin. Concurrently, debates on trading strategies persist, with Benlatreche (2024) examining technical analysis effectiveness, challenging the classical EMH assumptions.

Within this context, the present study revisits weak form efficiency for the Hong Kong Bursa HSI Index using an extensive recent sample of daily closing prices transformed into log returns. By combining traditional linear time series methods with nonlinear dependence tests, the article provides an integrated econometric assessment of market efficiency before, during, and after notable global shocks between 2015 and 2024.

Stemming from the above, the research problem of this study is encapsulated in the following main question:

To what extent does the Hang Seng Index (HSI) satisfy the conditions of weak-form market efficiency between 2015 and 2024, based on comprehensive linear and nonlinear diagnostics?

To address the research problem and the questions posed, the following hypotheses are formulated:

- **Main Null Hypothesis (H_0):** The Hong Kong Stock Exchange (represented by the HSI index) is weak-form efficient during the study period.
- **Main Alternative Hypothesis (H_1):** The Hong Kong Stock Exchange (represented by the HSI index) is not weak-form efficient during the study period.

2. Research Methods, toolsand measures:

The sample consists of 2,464 daily closing prices of the Hong Kong Bursa HSI Index from 2 January 2015 to 31 December 2024, as indicated in the EViews outputs. The continuous compounded (logarithmic) return is defined as

$$r_t = \ln P_t - \ln P_{t-1}$$

where is the closing price at day . This transformation stabilises variance and facilitates the application of asymptotic theory for many tests.

a. Descriptive Statistics and Normality

Before formal testing, descriptive statistics for are computed in EViews, including mean, median, standard deviation, skewness, kurtosis, and the Jarque–Bera (JB) statistic

$$\mathrm{JB} = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

where is the sample size, the sample skewness, and the sample kurtosis. Under the null of normality, is approximately distributed.

b. Autocorrelation, Partial Autocorrelation and Box–Ljung Test

Serial correlation is analysed using the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) for lags .

- *Autocorrelation function :*

$$\widehat{\rho_k} = \sum_{t=k+1}^{T}(r_t - \bar{r})(r_{t-k} - \bar{r}) \sum_{t=1}^{T}(r_t - \bar{r})^2$$

where is the sample mean and the number of observations.

- *Partial autocorrelation function*

The PACF at lag , denoted , is obtained from the Yule–Walker equations or an autoregression of order :

$$r_t = \alpha + \sum_{j=1}^{k} \phi_{kj} r_{t-j} + u_t$$

with representing the partial correlation between and controlling for intermediate lags.

- *Box–Ljung Q-statistic*

$$Q(m) = T(T+2) \sum_{k=1}^{m} \frac{\widehat{\rho_k^2}}{T-k}$$

which under the null of no autocorrelation up to lag approximately follows a distribution (Ljung & Box, 1978).

c. **Unit-Root Tests: ADF and PP**

To confirm stationarity of the return series, both Augmented Dickey–Fuller and Phillips–Perron tests are performed under three deterministic specifications: (i) none, (ii) constant, and (iii) constant plus trend, at level and differences as reported in the EViews table.

- *ADF regression and statistic*

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t$$

where is the series under test, is the lag length, and the null hypothesis (unit root) is tested using

$$\tau_{\text{ADF}} = \frac{\hat{\gamma}}{\text{SE}(\hat{\gamma})}$$

with non-standard critical values (Dickey & Fuller, 1979).

- *PP statistic*

The PP test uses the same regression as above but corrects for serial correlation and heteroskedasticity non-parametrically in the error term. The PP statistic can be written as

$$Z_\tau = \tau_{\text{DF}} - \frac{\widehat{\lambda_1} - \widehat{\lambda_0}}{2\widehat{\sigma^2}} \cdot \frac{T \cdot \text{SE}(\hat{\gamma})}{\hat{s}}$$

where is the Dickey–Fuller t-statistic, and are consistent estimates of the long-run and short-run variance, and is an estimator of the standard error (Phillips & Perron, 1988).

d. **Runs Test for Randomness**

The runs test examines randomness in the sign sequence of returns around the mean or median.
Let and be the number of positive and negative returns, respectively, , and the observed number of runs.

- *Expected runs and variance*

$$E(R) = \frac{2n_1 n_2}{N} + 1$$
$$\mathrm{Var}(R) = \frac{2n_1 n_2 (2n_1 n_2 - N)}{N^2 (N-1)}$$

- *Runs Z-statistic*

$$Z_{\text{runs}} = \frac{R - E(R)}{\sqrt{\mathrm{Var}(R)}}$$

which under the null of randomness is approximately standard normal (Jeran, 2023).

e. **BDS Test for Nonlinear Dependence**

The BDS test analyses whether a series is i.i.d. by comparing empirical correlation integrals across embedding dimensions .

- *Define the -dimensional embedding vectors*

$$X_t^{(m)} = (r_t, r_{t+1}, \dots, r_{t+m-1}), \quad t = 1, \dots, T-m+1$$

- *For a given distance , the correlation integral of dimension is*

$$C_m(\epsilon) = \frac{2}{(T-m+1)(T-m)} \sum_{t<s} 1\left(\left\| X_t^{(m)} - X_s^{(m)} \right\|_\infty < \epsilon \right).$$

Under i.i.d. behaviour,

- *BDS statistic*

$$\mathrm{BDS}(m, \epsilon) = \sqrt{T} \frac{C_m(\epsilon) - C_1(\epsilon)^m}{\widehat{\sigma_m}(\epsilon)},$$

which is asymptotically standard normal under the null (Brock et al., 1996).

f. **Variance-Ratio Test**

For a return series and horizon , define cumulative -period returns

$$Y_t^{(q)} = \sum_{j=0}^{q-1} r_{t-j}$$

Let be the variance of one-period returns and the variance of -period returns scaled by . The variance ratio is

$$VR(q) = \frac{\widehat{\sigma^2}(q)}{q\widehat{\sigma^2}(1)}$$

Under the random walk (martingale) null . Lo and MacKinlay'sheteroskedasticity-robust test statistic is

$$z_{VR}(q) = \frac{VR(q) - 1}{\sqrt{\widehat{\theta}(q)}}$$

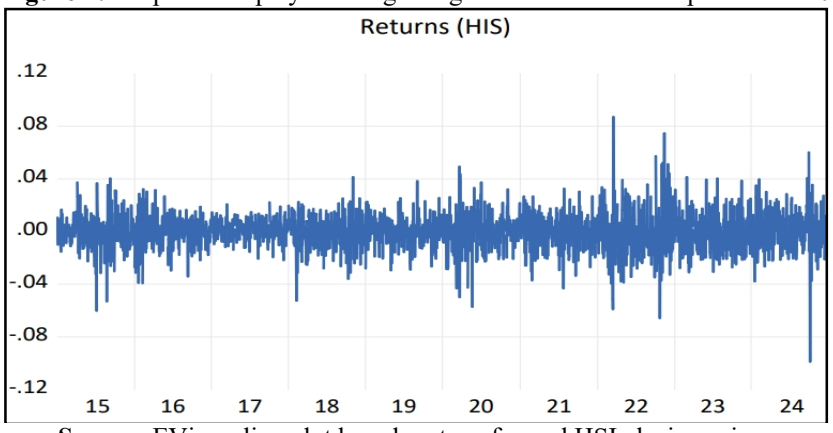
where is a consistent estimator of the variance of .

- ✓ **All analyses are conducted using EViews 13 software.**

3. Résultats:

Prior to applying standard econometric tests and determining statistical specifications for efficiency measurement, we conducted a visual analysis of the daily closing price returns. The time series represents the primary HSI index for the Hong Kong financial market. Data extracted from investing.com (2015–2024) was converted into daily returns using Equation ($r_t = \ln P_t \quad \ln P_{t-1}$). By calculating the natural logarithm of the current daily closing price against the previous one, we effectively applied first-degree differencing to eliminate random trend components from the series, as depicted in Figure 1.

Figure 1: Graphical display of Hong Kong Stock Market Index price returns.



Source: EViews line plot based on transformed HSI closing prices

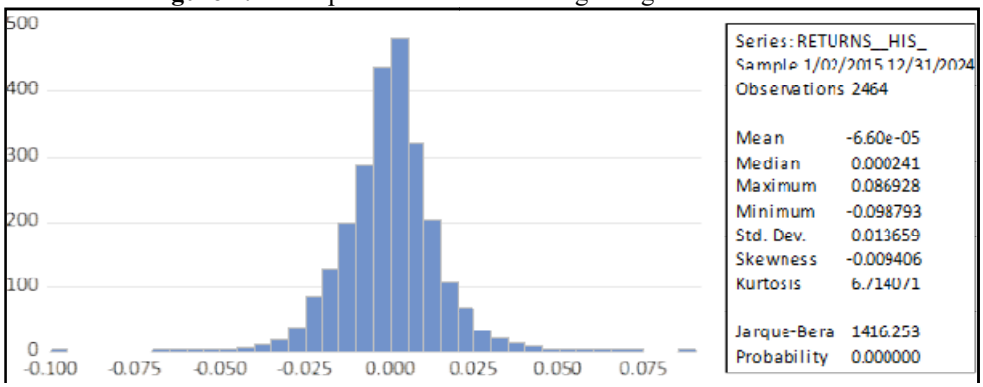
The plot of daily log-returns shows oscillation around zero with volatility clusters in 2015–2016, 2020, 2022, and late 2024. This volatility clustering—a stylized fact of financial markets—violates strict i.i.d. assumptions but remains compatible with weak-form efficiency provided the conditional mean is unpredictable.

Variable	2nd difference	1st difference	Level

3.1. Descriptive Statistics and Jarque–Bera Normality

The nature of the probability distribution of stock returns is critical to market efficiency theory. A normal distribution is a fundamental prerequisite for the Random Walk model. For a distribution to be considered normal, skewness must be zero, and kurtosis must equal or approximate three. Table 1 presents the normality test for the index observations based on the following hypothesis:
-H_0: The series follows a normal distribution.
-H_1: The series does not follow a normal distribution..

Figure 2: Descriptive Statistics for Hong Kong Market Returns.



Source: EViews histogram and summary statistics output for RETURNS__HIS

The return series has a mean very close to zero $(-6.60e^{-05})$ with a standard deviation of 0.0137. The kurtosis of 6.71 is substantially greater than 3, indicating leptokurtosis (fat tails). The Jarque-Bera test statistic is 1416.25 with a p-value of 0.0000, decisively rejecting the null hypothesis of a normal distribution.

3.2. Unit Root Tests : ADF and Phillips–Perron Tests

Stationarity of returns ensures that their statistical properties—such as unconditional mean and variance—are stable over time, providing a sound basis for subsequent tests of autocorrelation, randomness, and martingale behaviour that underpin weak-form efficiency diagnostics. (Fama, 1991).

	Intercept	Trend & Intercept	None	Intercept	Trend & Intercept	None	Intercept	Trend & Intercept	None
RETURNS_HIS	-22.43157 (0.0000)	-22.42698 (0.0000)	-22.43623 (0.0000)	-20.73131 (0.0000)	-20.72720 (0.0000)	-20.73559 (0.0000)	-48.92402 (0.0001)	-48.91659 (0.0000)	-48.93268 (0.0001)
	-800.7164 (0.0001)	-800.5193 (0.0001)	-800.9156 (0.0001)	-602.8107 (0.0001)	-602.6307 (0.0001)	-602.9757 (0.0001)	-48.92013 (0.0001)	-48.91263 (0.0000)	-48.92885 (0.0001)

Table 1 : ADF and PP Unit-Root Tests for RETURNS_HIS

Source: EViews unit-root (ADF and PP) output for RETURNS_HIS

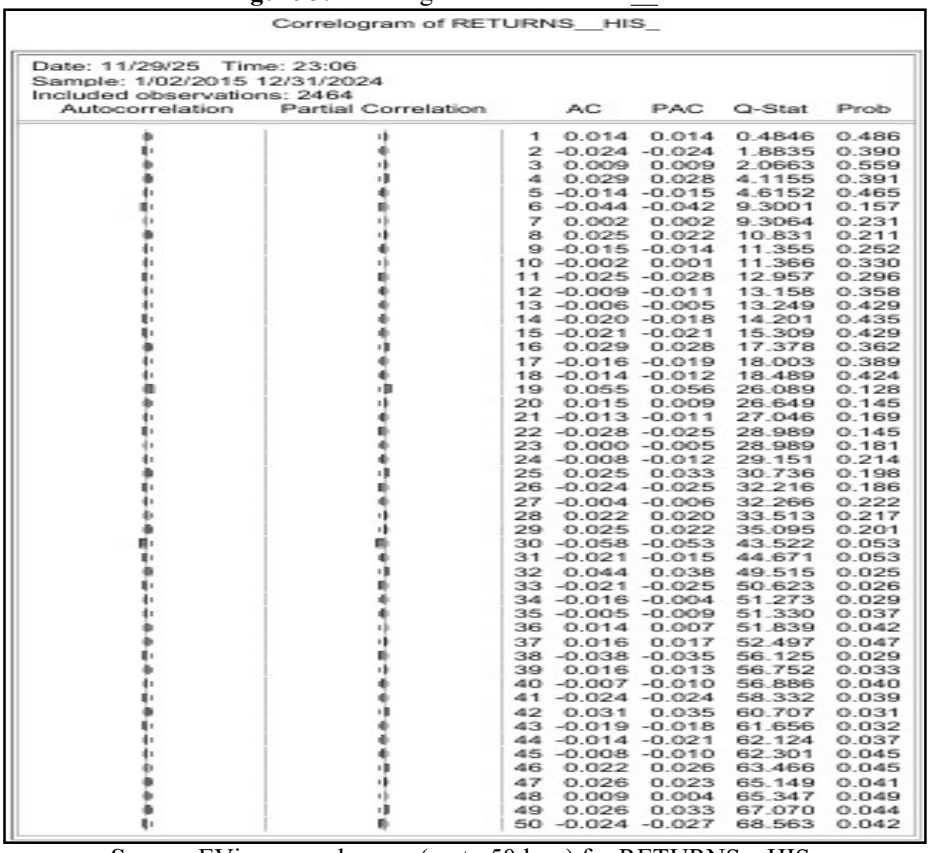
Across all specifications (none, intercept, trend and intercept), the ADF and PP statistics for RETURNS__HIS_ at the level are extremely negative (around −48.9) with p-values of 0.0000 or 0.0001. This leads to a clear rejection of the unit-root null at the 1% significance level. First and second differences show even more negative statistics, confirming strong stationarity. The fact that the series is stationary at level is entirely consistent with financial theory, which treats returns as stationary innovations even when prices may contain unit roots.

3.3. Serial Correlation (ACF/PACF and Ljung-Box)

In this section, we utilize autocorrelation tests to scrutinize the informational efficiency of the index. These tests determine whether the time series exhibits self-correlation. Specifically, the test evaluates the independence of past values over time. For the random walk hypothesis to hold regarding price returns, there must be zero correlation between current and historical returns (H_0). The test is based on:

- H_0: No autocorrelation exists in the series.
- H_1: Autocorrelation exists in the series.

Figure 3: Correlogram of RETURNS__HIS



Correlogram of RETURNS__HIS_

Date: 11/29/25 Time: 23:06
Sample: 1/02/2015 12/31/2024
Included observations: 2464

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.014	0.014	0.4846	0.486
		2	-0.024	-0.024	1.8835	0.390
		3	0.009	0.009	2.0663	0.559
		4	0.029	0.028	4.1155	0.391
		5	-0.014	-0.015	4.6152	0.465
		6	-0.044	-0.042	9.3001	0.157
		7	0.002	0.002	9.3064	0.231
		8	0.025	0.022	10.831	0.211
		9	-0.015	-0.014	11.355	0.252
		10	-0.002	0.001	11.366	0.330
		11	-0.025	-0.028	12.957	0.296
		12	-0.009	-0.011	13.158	0.358
		13	-0.006	-0.005	13.249	0.429
		14	-0.020	-0.018	14.201	0.435
		15	-0.021	-0.021	15.309	0.429
		16	0.029	0.028	17.378	0.362
		17	-0.016	-0.019	18.003	0.389
		18	-0.014	-0.012	18.489	0.424
		19	0.055	0.056	26.089	0.128
		20	0.015	0.009	26.649	0.145
		21	-0.013	-0.011	27.046	0.169
		22	-0.028	-0.025	28.989	0.145
		23	0.000	-0.005	28.989	0.181
		24	-0.008	-0.012	29.151	0.214
		25	0.025	0.033	30.736	0.198
		26	-0.024	-0.025	32.216	0.186
		27	-0.004	-0.006	32.266	0.222
		28	0.022	0.020	33.513	0.217
		29	0.025	0.022	35.095	0.201
		30	-0.058	-0.053	43.522	0.053
		31	-0.021	-0.015	44.671	0.053
		32	0.044	0.038	49.515	0.025
		33	-0.021	-0.025	50.623	0.026
		34	-0.016	-0.004	51.273	0.029
		35	-0.005	-0.009	51.330	0.037
		36	0.014	0.007	51.839	0.042
		37	0.016	0.017	52.497	0.047
		38	-0.038	-0.035	56.125	0.029
		39	0.016	0.013	56.752	0.033
		40	-0.007	-0.010	56.886	0.040
		41	-0.024	-0.024	58.332	0.039
		42	0.031	0.035	60.707	0.031
		43	-0.019	-0.018	61.656	0.032
		44	-0.014	-0.021	62.124	0.037
		45	-0.008	-0.010	62.301	0.045
		46	0.022	0.026	63.466	0.045
		47	0.026	0.023	65.149	0.041
		48	0.009	0.004	65.347	0.049
		49	0.026	0.033	67.070	0.044
		50	-0.024	-0.027	68.563	0.042

Source:EViewscorrelogram (up to 50 lags) for RETURNS__HIS.

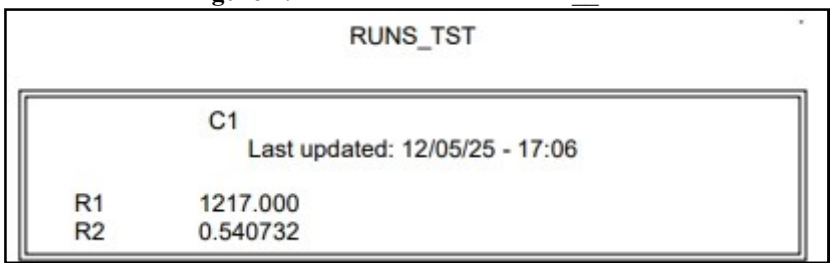
The correlogram shows autocorrelation(AC) and partial autocorrelation (PAC) coefficients at various lags are mostly small, with the majority within the 95% confidence bands. The Ljung-Box Q-statistics for lags up to 45 have high p-values (e.g., Q(5)=4.62, p=0.465; Q(10)=11.36, p=0.330), failing to reject the null hypothesis of no serial correlation up to those lags. This suggests an absence of significant linear dependence.

3.4. Runs Test of Randomness

Non-parametric tests are statistical methods that do not rely on assumptions about data distribution and are less sensitive to outliers. This makes them highly effective for testing the random walk hypothesis. Prominent types include the Runs test and the test for linear independence (BDS test). These are notable for their simplicity and applicability, particularly when normality and homoscedasticity are absent. The Runs test is based on the hypothesis:

-H_0: The sequence follows a random process.
-H_1: The sequence does not follow a random process.

Figure 4: Runs Test for RETURNS__HIS



Source: EViews runs-test output based on signs of RETURNS__HIS.

positive returns, negative returns, so . The observed number of runs is . The expected number of runs under randomness is with standard deviation . The resulting test statistic is ($Z_{runs} = -0.9683$)with a two-sided p-value of

0.540. Because this p-value is far above 0.05, the null of randomness in the sequence of positive and negative returns cannot be rejected. The direction of daily HSI returns therefore appears to fluctuate randomly, providing support for weak-form efficiency at the level of sign changes.

3.5. BDS Test for Nonlinear Dependence

The BDS test is a robust tool for detecting linear trends within time-series data. This test operates on the following hypothesis:
- H_0: The time series is linearly independent.
- H_1: The time series is not linearly independent.

Figure 5: BDS Test for RETURNS__HIS

BDS Test for RETURNS__HIS_
Date: 11/30/25 Time: 16:58
Sample: 1/02/2015 12/31/2024
Included observations: 2464

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.007923	0.001689	4.689844	0.0000
3	0.017379	0.002682	6.479758	0.0000
4	0.026389	0.003191	8.270857	0.0000
5	0.033106	0.003322	9.965597	0.0000
6	0.036430	0.003200	11.38344	0.0000

Raw epsilon	0.018366		
Pairs within epsilon	4273746.	V-Statistic	0.703926
Triples within epsilon	8.04E+09	V-Statistic	0.537434

Dimension	C(m,n)	c(m,n)	C(1,n-(m-1))	c(1,n-(m-1))	c(1,n-(m-1))^k
2	1525382.	0.503102	2133554.	0.703690	0.495179
3	1107756.	0.365657	2131466.	0.703572	0.348278
4	821117.0	0.271262	2129374.	0.703453	0.244873
5	621044.0	0.205333	2127571.	0.703429	0.172227
6	476038.0	0.157518	2125661.	0.703370	0.121088

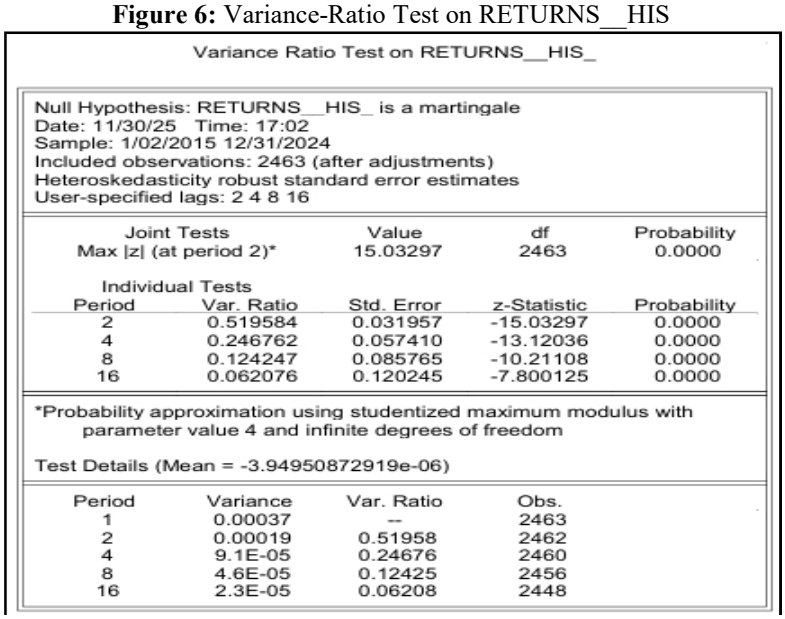
Source:EViews BDS-test output for RETURNS__HIS_.

The BDS test results are striking.For embedding dimensions (m) from 2 to 6, the BDS statistics are positive and highly significant (all p-values = 0.0000). This provides strong evidence against the null hypothesis that the returns are IID, indicating the presence of non-linear dependence or structure in the data.

3.6. Variance-Ratio Test and the Martingale Property

Generally, variance-ratio tests are considered more precise than autocorrelation tests in determining whether a time series satisfies the random walk hypothesis. While autocorrelation measures the link between observations, the variance ratio measures the variance of the series against a linear benchmark (e.g., a low variance implies points are very close to a linear pattern). The test is based on:
-H_0: The sequence follows a random process (Variance Ratio value equals one).
- H_1: The sequence does not follow a random process.

Figure 6: Variance-Ratio Test on RETURNS__HIS



Variance Ratio Test on RETURNS__HIS_

Null Hypothesis: RETURNS__HIS_ is a martingale
Date: 11/30/25 Time: 17:02
Sample: 1/02/2015 12/31/2024
Included observations: 2463 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	15.03297	2463	0.0000

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.519584	0.031957	-15.03297	0.0000
4	0.246762	0.057410	-13.12036	0.0000
8	0.124247	0.085765	-10.21108	0.0000
16	0.062076	0.120245	-7.800125	0.0000

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = -3.94950872919e-06)

Period	Variance	Var. Ratio	Obs.
1	0.00037	--	2463
2	0.00019	0.51958	2462
4	9.1E-05	0.24676	2460
8	4.6E-05	0.12425	2456
16	2.3E-05	0.06208	2448

Source: EViews variance-ratio output using heteroskedasticity-robust standard errors.

The variance ratio test results robustly reject the martingale null hypothesis.For all tested holding periods (q=2, 4, 8, 16), the variance ratios are significantly less than 1 (e.g., VR(2)=0.5196) with z-statistics ranging from -7.80 to -15.03 and p-values of 0.0000. This indicates that the variance of q-period returns grows at less than a linear rate, implying negative serial correlation in returns.

4. Discussion :

The combined results from descriptive statistics, unit-root checks, autocorrelation diagnostics, runs test, BDS test, and variance-ratio analysis provide a balanced assessment of HSI weak-form efficiency. Returns are stationary with near-zero mean and finite variance, and their leptokurtic, heavy-tailed shape and volatility clustering match well-known global stylised facts and previous evidence on Hong Kong and Asian markets.
Linear tests show only small and mostly short-horizon autocorrelations. Although the Ljung–Box statistic detects some joint dependence at longer lags, these correlations remain modest, and the runs test supports randomness in return signs. Together, these outcomes suggest that simple linear forecasting rules are unlikely to yield meaningful excess returns, broadly consistent with the spirit of weak-form efficiency.

In contrast, the BDS test reveals strong nonlinear dependence, indicating higher-order structure typically associated with time-varying volatility, structural breaks, or regime changes observed during major financial and geopolitical episodes. While such behaviour violates strict i.i.d. assumptions, it does not automatically imply exploitable return predictability.

The variance-ratio findings present the clearest deviation from a martingale difference process: HSI returns exhibit marked mean reversion over multi-day horizons, with variance ratios falling sharply as the horizon lengthens and significantly negative z-statistics. This behaviour mirrors earlier evidence for US and Asia-Pacific markets.

Overall, the HSI shows a mixed efficiency profile. Short-run randomness and weak linear dependence suggest near-efficiency, while nonlinear features and mean-reverting patterns point to subtle yet statistically significant deviations from a pure random walk. Still, the economic relevance of such deviations may be limited by transaction costs, market frictions, and the joint-hypothesis problem, which complicates interpretations of efficiency tests.

The analysis remains constrained by the use of daily univariate returns and a fixed set of tests, without explicitly modelling major events or structural breaks. Future work could employ intraday data, volatility models such as GARCH or stochastic-volatility specifications, rolling BDS/VR procedures to capture time variation, and cointegration or spillover analyses to explore the HSI's interactions with mainland Chinese and global markets.

5. Conclusion:

Using Using daily log-returns for the HSI over 2015–2024 and a broad set of econometric tests, the study provides an updated view of the index's weak-form efficiency. The data are stationary with near-zero mean and show heavy tails and volatility clustering typical of financial markets. Linear diagnostics such as ACF/PACF, Ljung–Box statistics, and the runs test point to very limited short-term linear predictability, as return signs behave largely at random.

However, the BDS test uncovers strong nonlinear dependence, and the heteroskedasticity-robust variance-ratio test consistently indicates mean reversion across 2- to 16-day horizons, rejecting the martingale difference hypothesis. This means that although past information is incorporated quickly enough to prevent simple trading strategies from earning persistent abnormal returns, the index does not fully conform to a strict random-walk structure.

Overall, the HSI appears close to weak-form efficiency on a daily basis, yet it displays subtle but statistically significant deviations from pure i.i.d. behaviour. For practitioners, these patterns imply that only advanced models capable of capturing nonlinear and horizon-dependent dynamics might extract limited predictive value, with economic gains likely constrained by costs and risk considerations. For policymakers, the findings highlight the need to preserve transparency, liquidity, and strong market infrastructure to sustain high informational efficiency amid global uncertainty.

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7. Appendices:

Appendice 01 : Augmented Dickey-Fuller Test

Null Hypothesis: RETURNS__HIS_ has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic - based on SIC, maxlag=26)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-48.91659	0.0000
Test critical values:	1% level	-3.961770	
	5% level	-3.411632	
	10% level	-3.127688	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(RETURNS__HIS_)

Method: Least Squares

Date: 11/29/25 Time: 00:38

Sample (adjusted): 1/05/2015 12/31/2024

Included observations: 2463 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RETURNS__HIS_(-1)	-0.986040	0.020158	-48.91659	0.0000
C	9.91E-05	0.000551	0.179930	0.8572
@TREND("1/02/2015")	-1.37E-07	3.87E-07	-0.353347	0.7239

R-squared	0.493080	Mean dependent var	-3.95E-06
Adjusted R-squared	0.492668	S.D. dependent var	0.019184
S.E. of regression	0.013664	Akaike info criterion	-5.746838
Sum squared resid	0.459316	Schwarz criterion	-5.739762
Log likelihood	7080.231	Hannan-Quinn criter.	-5.744267
F-statistic	1196.417	Durbin-Watson stat	1.998972
Prob(F-statistic)	0.000000		