Is Cointegration Among Stock Markets Robust to Currency Conversions?

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1. Introduction

Financial-market indices are indispensable barometers of macro-economic conditions, investor sentiment, and systemic stress. In the short run their returns are empirically non-Gaussian—exhibiting skewness, excess kurtosis, and clustered volatility—but a more consequential debate concerns the long-run behaviour of index levels. Do national equity prices share a common stochastic trend, and is that conclusion robust once those prices are re-expressed in alternative currencies? Despite three decades of research, no consensus has emerged. Working with five developed markets, Kasa (1992) reported his 5 countries are driven by a single stochastic trend—but only after converting each series into real U.S. dollars. By contrast, Richards (1995) and DeFusco, Geppert & Tsetsekos (1996) found no cointegration for much larger panels, even though they employed the same numeraire. Most recently, Babaei, Hübner & Muller (2023) demonstrated that cointegration strength fluctuates with global-uncertainty regimes, implying that any inference about long-run linkage may be doubly conditional—on when one looks and on how indices prices are transformed.

This study revisits the problem with a uniformly specified, post-crisis dataset that spans three major market regimes: the 2008 Global Financial Crisis, the 2011–12 Euro-area debt episode, and the 2020–22 COVID-19 turmoil. We analyse eight flagship indices—S&P 500, FTSE 100, DAX, MIB, Hang Seng, S&P/TSX, SSE Composite, and STI—chosen to represent the United States, Europe's core and periphery, North America, and two leading Asian financial centres plus mainland China. Johansen cointegration ranks are estimated under five numeraires (local currency, USD, CAD, EUR, HKD) with identical lag and deterministic choices, so that any change in rank can be attributed solely to the currency of measurement.

By systematically combining currency-controlled cointegration tests with higher-moment diagnostics, the paper delivers a clean benchmark for assessing whether earlier disagreements are rooted in true economic segmentation or in the accounting units applied to price data. The resulting evidence clarifies how exchange-rate conversions condition statistical inferences about long-run co-movement and offers a reference point for future empirical work on international market integration.

2. Literature Review

Financial market indices serve as crucial instruments for gauging economic conditions, guiding investment strategies, and assessing investor sentiment. Investors, fund managers, and policymakers rely heavily on these indices to make informed decisions regarding portfolio diversification, risk management, and macroeconomic forecasting. Understanding the statistical distribution of market index returns is especially pivotal, as it profoundly impacts financial modeling, risk assessment, and theoretical assumptions underlying asset pricing models.

Empirical studies dedicated explicitly to the statistical properties of market returns have consistently challenged the assumption of normality. Jarque and Bera (1987) developed widely accepted tests for detecting deviations from normality by incorporating measures of skewness and kurtosis. These tests have become standard in financial econometrics, underpinning numerous subsequent studies. Andersen et al. (2001) and Cont (2001) extended this literature by demonstrating robust evidence of volatility clustering and heavy-tailed distributions in financial returns. Such characteristics imply that extreme market events occur more frequently than predicted under normal distribution assumptions, significantly influencing risk modeling and financial forecasting.

Richards (1995), drawing on Granger (1986), notes that under the Efficient Market Hypothesis the prices of speculative, non-yielding assets (e.g., gold and silver) cannot be cointegrated; although equity indices differ because dividends embed a yield component, this benchmark cautions that we should not, a priori, expect strong cointegration across stock markets.

In this regard, many researchers have provided a lot of reference materials, but the results are mixed. The seminal contribution is Kasa (1992), who used Johansen's (1991) maximum-likelihood procedure to test cointegration among five major markets. He found a single global stochastic trend—but only after converting each index into a real U.S.-dollar numeraire. However, Richards (1995) broadened the panel to sixteen markets—even in real dollars—and failed to reject the null of no cointegration.

DeFusco, Geppert, and Tsetsekos (1996) analyse weekly index levels from January 1989 through May 1995 after converting each series to U.S. dollars. When they apply Johansen's procedure to an Asia-Pacific block that includes the United States, Korea, the Philippines, Taiwan, Malaysia, and

Thailand, they are unable to reject the null of no cointegration. They obtain the same rank-zero result for the two additional regional groupings in their sample, leading them to characterise international equity markets of that era as segmented rather than integrated.

Masih and Masih (1999) take a higher-frequency approach, using daily data from 14 February 1992 to 19 June 1997 denominated in real U.S. dollars (the authors do not spell out their daily deflation procedure). For a broader set of eight OECD and Asian markets—United States, Japan, United Kingdom, Germany, Singapore, Malaysia, Hong Kong, and Thailand—they do detect long-run linkage, but identify only one cointegrating vector. Consequently, seven independent stochastic trends remain, implying that most of the long-run variation is still market-specific.

Sharma and Wongbangpo (2002) analyse monthly stock-index levels for the five original ASEAN members over the period January 1986 to December 1996, keeping each series in its local-currency denomination. Using Johansen's procedure, they uncover a single long-run equilibrium that links the markets of Indonesia, Malaysia, Singapore, and Thailand, while the Philippine exchange remains outside the cointegrating relation. Because only one vector is identified for the four participating markets, three independent stochastic trends persist, indicating that a substantial portion of long-run movement is still country-specific.These results may imply that long-run cointegration relationship is sample-specific and heavily dependent on exchange-rate treatment.

However, Click and Plummer (2005) pointed out in their research, cointegration tests detect the same long-run link in both daily and weekly samples, and that this result holds regardless of whether prices are quoted in local currency or U.S. dollars, is conceptually reassuring. Despite appearing counter-intuitive from a theoretical or institutional standpoint, the outcome probably signals a genuinely robust connection among the underlying equity markets—one that remains intact even after exchange-rate movements are considered.

Recognising that long-run linkages may evolve, recent papers employ rolling or state-space extensions of Johansen's test. The latest contribution, Babaei, Hubner and Muller (2023), applies a Kalman-filter cointegration model and confirms that both the existence and strength of long-run linkages hinge on global-uncertainty regimes and currency denomination. Collectively, these studies underscore an unresolved issue: cointegration evidence may vanish because of different currency numeraire.

To address these gaps, this study provides an updated comparative evaluation of market index returns from selected developed and emerging countries spanning 2005 to 2025, analyzing daily, weekly, and monthly data frequencies. The research utilizes descriptive statistics (specifically skewness and excess kurtosis) and applies the Jarque–Bera normality test, known for its effectiveness in identifying deviations from normal distribution through simultaneous consideration of skewness and kurtosis.

In parallel, we re-examine Johansen cointegration for eight indices (S&P 500, FTSE 100, S&P/TSX, MIB, DAX, Hang Seng, STI, SSE) in local-currency and other numeraires log levels, using an identical lag-selection protocol and deterministic specification. This approach allows us to quantify how sensitive long-run integration is to exchange-rate conversion, thereby extending the Kasa–Richards debate with two additional decades of data.

3. Data

For the return-distribution analysis, we work with continuously compounded log-returns derived from local-currency closing prices. Seven equity markets are covered—FTSE 100 (UK), S&P/TSX Composite (Canada), Straits Times Index (Singapore), Hang Seng Index (Hong Kong), DAX (Germany), MIB (Italy) and SSE Composite (China)—at daily, weekly and monthly frequencies over 3 May 2005 to 1 April 2025. All price data are downloaded from LSEG Refinitiv, and returns are computed as first differences of log prices in the respective domestic currencies; no currency conversion is required at this stage because the distribution exercise focuses exclusively on local-market dynamics.

For the cointegration tests, we revert to index price levels and expand the sample to include the S&P 500. The seven non-US indices are again taken from Refinitiv in both local-currency and multi-currency (USD, CAD, EUR, HKD) quotations. The S&P 500 comes from Robert Shiller's database in USD and is converted into the other numeraires via an implied-exchange-rate approach: on each month-end date, the USD-to-currency k exchange rate is backed out from a Refinitiv index quoted in both currencies (e.g., $FX_{\frac{EUR}{USD}} = \frac{FTSE_{EUR}}{FTSE_{USD}}$), and the S&P 500 USD close is divided by this rate to obtain, CAD, EUR and HKD series. All conversions are executed in Excel to ensure perfect date alignment, yielding

Table 1: Mean and Standard Deviation of Percentage Log Returns.

Index	***Daily***		***Weekly***		***Monthly***	
	Mean	SD	Mean	SD	Mean	SD
FTSE 100	0.0176	1.1095	0.0757	2.3545	0.3015	3.7569
S&P/TSX	0.0255	1.0790	0.1117	2.2588	0.4775	3.8644
STI	0.0183	1.0182	0.0849	2.2844	0.3882	4.7849
Hang Seng	0.0217	1.5001	0.0924	3.0159	0.4097	6.2464
DAX	0.0416	1.3095	0.1943	2.9235	0.8101	5.1565
MIB	0.0155	1.5006	0.0621	3.2023	0.2555	5.9673
SSE	0.0337	1.4952	0.1603	3.2043	0.7494	7.2839

an eight-index, five-currency panel for the period May 2005 to March 2025 that is fully comparable across markets.

To investigate temporal effects on distributional properties, this article constructs three return series for each index:

$$\text{Daily log-returns:} r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$$

$$\text{Weekly log-returns: } r_{weekly} = \ln\left(\frac{p_{Friday\ close}}{p_{Last\ Friday\ close}}\right)$$

$$\text{Monthly log-returns: } r_{monthly} = \ln\left(\frac{p_{End\ of\ the\ month\ close}}{p_{End\ of\ last\ month\ close}}\right)$$

Logarithmic returns are chosen for their simple time-additivity and widespread use in financial econometrics.

Table 1 provides descriptive statistics of daily, weekly, and monthly percentage log returns for seven major international equity indices (FTSE 100, S&P/TSX, STI, Hang Seng, DAX, MIB, and SSE) over the period from May 2005 to March 2025. The table reports means and standard deviations across different sampling frequencies, illustrating how returns and volatility systematically vary as the data are aggregated from daily to monthly observations. Daily returns typically show the lowest average return coupled with relatively lower volatility compared to weekly and monthly frequencies. As expected, standard deviations increase notably with longer sampling intervals, reflecting greater accumulated price variation over extended horizons. These patterns underscore the importance of carefully considering sampling intervals when analyzing and interpreting financial market data.

4. Empirical Analysis: Methods and Findings

4.1 Distribution analysis

For each return series, this article computes

$$\text{Skewness: } S = \frac{\frac{1}{n}\sum_{t=1}^{n}(r_t-\overline{r})^3}{\left(\frac{1}{n}\sum_{t=1}^{n}(r_t-\overline{r})^2\right)^{\frac{3}{2}}},$$

$$\text{Kurtosis: } K = \frac{\frac{1}{n}\sum_{t=1}^{n}(r_t-\overline{r})^4}{\left(\frac{1}{n}\sum_{t=1}^{n}(r_t-\overline{r})^2\right)^{2}},$$

Where n is the sample size, $r_t$are the log-returns and $\overline{r}$ are the sample mean. Skewness quantifies the degree of asymmetry and kurtosis quantifies tail-thickness in each market's return distribution prior to formal testing. For example, a normal distribution has skewness of zero and kurtosis of three.

To assess departures from normality in each return series, this article employs the Jarque-Bera (JB) test (Jarque & Bera, 1980). The JB statistic is defined as

$$JB = \frac{n}{6}S^2 + \frac{n}{24}(K-3)^2,$$

where n is the sample size, S is the sample skewness and K is the sample kurtosis. Under the null hypothesis H_0: returns are normally distributed. We reject H_0 at level α if

$$JB > x_{1-\alpha}^2$$

This article reports p-values for each test and adopts a 5% significance threshold. All calculations were performed in EViews, ensuring reproducibility. Sample skewness and kurtosis were computed using their unbiased estimators. Tests were conducted separately for each index at each frequency.

Although the JB test is based on large-sample theory, we verify that each series has $n > 200$ observations. Moreover, we compare results across frequencies to ensure that the conclusion of non-normality is robust to choice of sampling interval.

At the daily frequency, six of seven indices exhibit negative skewness, indicating a tendency toward more extreme negative returns. The S&P/TSX stands out with the most pronounced left-skew (-0.687454), while the Hang Seng is the only index with positive skewness (0.247009), this suggests a mild bias toward extreme positive days. All indices display very high kurtosis (8.249177 - 22.26349),

Table 2: Skewness and Kurtosis of Percentage Log Returns.

Index	*Daily*		*Weekly*		*Monthly*	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
FTSE 100	–0.2086	13.258	–1.0466	14.574	–0.5332	4.219
S&P/TSX	–0.6875	22.263	–1.0586	12.617	–1.0126	6.796
STI	–0.1536	10.849	–0.0819	10.796	–0.4966	7.841
Hang Seng	+0.2470	10.867	+0.0081	5.185	+0.0483	4.788
DAX	–0.0203	11.516	–0.8098	10.356	–0.4959	4.492
MIB	–0.4397	11.887	–1.0862	9.016	–0.1583	4.578
SSE	–0.4108	8.249	–0.0245	5.794	–0.1086	5.088

reflecting heavy tails and an elevated probability of extreme returns relative to the Gaussian benchmark. The S&P/TSX again shows the fattest tails (kurtosis = 22.26349), underscoring its high daily return volatility.

Moving to weekly data, skewness magnitudes generally increase: the FTSE 100, S&P/TSX, DAX and MIB all exceed –0.80, with the S&P/TSX (-1.0586) and MIB (-1.0862) the most heavily left-skewed. The Hang Seng's skewness becomes essentially zero (0.008123), indicating near symmetry at this horizon. Kurtosis declines relative to the daily series. However, it remains materially above zero (5.184688 - 14.57404), confirming persistent leptokurtic behavior even at weekly scale.

At the monthly frequency, the magnitude of both skewness and kurtosis further attenuates. All indices retain mild negative skewness (-0.158346 to –1.012571), except Hang Seng which remains slightly positive (0.048310). Kurtosis falls to the range 4.218501 to 7.841082, indicating that while tail-risk diminishes with longer horizons, monthly returns continue to exhibit heavier tails than a normal distribution. Notably, the S&P/TSX still shows the most extreme skew (-1.012571).

Cont (2001) states that as returns are computed over increasingly longer intervals (larger time scales), their distribution progressively approximates normality, particularly, the distribution shape evolves distinctly across different time scales. From kurtosis side, most of indices are similar to this conclusion. With the exception of the FTSE100, the kurtosis of all the other indices decreases as the time scale increases, getting closer and closer to 3 (the kurtosis of the normal distribution). However, the behaviour of skewness deviates from this aggregation pattern. When the horizon is extended from daily to weekly, the skewness of every index except the STI, Hang Seng, and SSE moves farther from the Gaussian benchmark of zero. A further extension from daily to monthly shows an even stronger divergence: with the exception of the MIB and SSE, the skewness of all other indices shifts further away from normality.

Across all frequencies, the S&P/TSX consistently demonstrates relatively strongest left-skewed, suggesting a higher likelihood of extreme negative moves. The Hang Seng alone occasionally displays slight positive skew, particularly at daily and monthly intervals. Overall, these moment-based diagnostics preliminary confirm that none of the indices follow a Gaussian return distribution.

4.2 Jarque-Bera Test

At the daily frequency, all market indices strongly reject the null hypothesis of normality, as indicated by exceptionally large JB statistics. The S&P/TSX exhibits the highest JB statistic (77655.98), suggesting extreme deviations from normality, while the lowest JB statistic (5592.83, SSE) still substantially exceeds conventional critical values. Corresponding p-values are uniformly less than 0.001, confirming statistically significant departures from Gaussian assumptions across all indices.
Weekly returns also exhibit statistically significant departures from normality, although the JB statistics notably decrease compared to daily returns. The highest JB statistic among weekly data is observed for FTSE 100 (5988.96), and the lowest for Hang Seng (206.6365). All p-values remain extremely small ($p < 0.001$), consistently rejecting the hypothesis of normality at conventional significance levels.

At monthly frequency, the JB statistics further decline yet remain clearly significant for all indices. JB values range from 25.69725 (MIB) to 242.1886 (STI), each far exceeding the 1% critical value of the Chi-square distribution. The resulting p-values are also below 0.001 for all indices, indicating persistent non-normality even at the longest examined interval.

The Jarque-Bera test results conclusively reject the normality assumption for daily, weekly and monthly returns across all seven indices. These empirical findings align with the previously reported skewness and kurtosis characteristics, emphasizing significant asymmetry and pronounced tail risks in market returns. Such persistent asymmetry and fat tails concur with the stylised facts catalogued by Cont (2001).

Table 3: Jarque-Bera Test and P-value of Percentage Log Returns.

Index	***Daily***		***Weekly***		***Monthly***	
	JB Statistic	P-value	JB Statistic	P-value	JB Statistic	P-value
FTSE 100	22,106.44	0.000000	5,988.956	0.000000	26.00189	0.000002
S&P/TSX	77,655.98	0.000000	4,197.686	0.000000	183.5808	0.000000
STI	12,899.49	0.000000	2,632.012	0.000000	242.1886	0.000000
Hang Seng	12,706.23	0.000000	206.637	0.000000	31.79007	0.000000
DAX	15,290.30	0.000000	2,455.975	0.000000	31.82201	0.000000
MIB	16,810.34	0.000000	1,770.978	0.000000	25.69725	0.000003
SSE	5,692.83	0.000000	329.991	0.000000	43.68824	0.000000

As an initial step in the analysis, this study examines the univariate properties of the eight market indices in terms of their statistical distributions. These properties, including measures of skewness, kurtosis, and the results of normality tests such as the Jarque-Bera test, offer insight into the general behavior of market returns. Specifically, all markets exhibit significant departures from normality, with persistent negative skewness and high kurtosis, suggesting non-Gaussian distributions characterized by higher risks of extreme price movements.

However, it is important to emphasize that this descriptive analysis serves primarily as a preliminary diagnostic step. While it provides useful context and helps us understand the statistical properties of the individual markets, it is not the central focus of this study. The main objective of this paper is to investigate whether long-run cointegration relationships among these equity markets are robust to currency conversions, an analysis that takes center stage in the subsequent sections. The univariate analysis is therefore intended to set the stage for understanding the broader, more complex dynamics explored through the cointegration tests.

4.3 Cointegration analysis

Before a cointegration analysis is meaningful, each log-price series must be shown to be integrated of order one. We therefore estimate the Augmented Dickey–Fuller (ADF) regression (intercept and trend) for every index in both numeraires:

$$\Delta L_t = \alpha + \beta t + \rho L_{t-1} + \sum_{j=1}^{k} \gamma_j \, \Delta L_{t-j} + \varepsilon_t \ ,$$

Where L_t is the log level, t is a linear time trend, and $\varepsilon_t \sim i.i.d.(0,\, \sigma^2)$. The null hypothesis $H_0\!: \rho = 0$ corresponds to a unit root.

All Augmented Dickey–Fuller tests are performed on the logarithmic level series. Augmenting lag lengths were selected by minimizing Schwarz's Bayesian information criterion (BIC) within a maximum augmenting lag length of 12. Using the 5 % MacKinnon critical value of –3.429, none of the test statistics in Table 4 are more negative than the threshold; the null hypothesis of a unit root therefore cannot be rejected for any of the eight equity indices, regardless of numeraire. Even the most negative statistic (–3.351 for the S&P/TSX in USD) falls short of the rejection region, whereas several series—most notably the MIB and the CAD-denominated FTSE 100—exhibit values above –2.0, indicating a pronounced degree of non-stationarity.

Empirically, several indices yield more-negative ADF statistics once they are translated into a common foreign currency. Currency conversion adds the log change of the exchange rate to the equity price process, thereby altering the series' autoregressive structure. Thus, re-denomination can strengthen or weaken evidence against the unit-root null. Nevertheless, the incremental variation is insufficient to alter the integration order; each series remains integrated of order one, I(1), under all five numeraires (Local, USD, CAD, EUR, and HKD).

After verifying those indices are I(1), estimating the Vector-Error-Correction Model

$$\Delta L_t = \Gamma_1 \Delta L_{t-1} + \cdots \Gamma_{j-1} \Delta L_{t-j+1} + \Pi L_{t-j} + \mu + u_t$$

where j is the lag order of underlying VAR. Γ is the short-run coefficient matrices. Π is the long-run coefficient matrix. The rank r = rank(Π) is the number of cointegrating relations. μ is the deterministic intercept and u_t is the error vector assumed i.i.d. with mean zero.

For each numeraire, this article computes Johansen's both Trace and Maximum-Eigenvalue statistics. Sequential testing proceeds from r_0= 0 upward; Mackinnon-Haug-Michelis (1999) finite-sample critical values are employed. Note that Trace test and Maximum-Eigenvalue test have different hypotheses. Trace test has a null hypothesis that $H_0\!: rank(\,\Pi\,) \le r$, with an alternative hypothesis $H_1\!: rank(\,\Pi\,) > r$. Whereas Maximum-Eigenvalue test has a null hypothesis that $H_0\!: rank(\,\Pi\,) = r$, and the alternative hypothesis is that $H_1\!: rank(\,\Pi\,) = r + 1$.

Table 4. ADF Statistics Under BIC-selected Lag Length (5% critical value = -3.429).

Index \ Numeraire	***Local***	***USD***	***CAD***	***EUR***	***HKD***
FTSE 100	-2.884	-2.552	-1.719	-2.001	-2.529
S&P/TSX	–2.617	-3.351	-2.617	-3.192	-3.328
STI	–3.063	-3.113	-2.793	-2.840	-3.096
Hang Seng	–3.023	-3.045	-2.380	-2.691	-3.023
DAX	–2.809	-3.305	-2.383	-2.809	-3.288
MIB	–1.200	-1.519	-1.126	-1.200	-1.517
SSE	–3.108	-3.308	-2.841	-3.146	-3.295
S&P 500	–2.348	-2.348	-2.182	-2.204	-2.344

To lend uniformity to the analysis, a lag length of 4 is used for all series. Meanwhile, given efficient markets, we do not expect stock returns to exhibit much autocorrelation, even in the aggregate returns measured by market indexes. This is especially so in low frequency data such as monthly, quarterly and annually data. Hence the EViews default of 4 lags should be adequate.

The Johansen cointegration tests conducted in this study reveal distinct patterns dependent upon the currency denomination of the indices. Our analysis, covering eight equity markets (FTSE 100, S&P/TSX, STI, Hang Seng, DAX, MIB, SSE Composite, and S&P 500) from May 2005 to March 2025, demonstrates no evidence of cointegration when analysed in local currencies. Specifically, both trace and maximum-eigenvalue tests fail to reject the null hypothesis of no cointegration at conventional significance levels, suggesting that 8 indices have no long-run relationship, and each evolves according to its own stochastic trend. This finding implies that national equity indices, when expressed in their respective domestic currencies, are primarily influenced by country-specific factors, such as domestic economic policies, market-specific shocks, local investor sentiment, and regulatory environments, which collectively prevent significant cross-border convergence in equity price movements.

However, when indices are converted into USD, CAD, EUR, or HKD, our results consistently indicate evidence of cointegration. Specifically, under USD, CAD, EUR, and HKD denominations, both trace and maximum-eigenvalue tests reject the null hypothesis of no cointegration, indicating the presence of at least one cointegrating vector among the eight markets. Furthermore, the tests also reject

Table. 5 shows the results of Cointegration analysis using different numeraires

Rank hypothesis	*Trace stat.*	*Trace 5 % CV*	*Max-Eig stat.*	*Max-Eig 5 % CV*
Panel A – Local currency				
None	171.9601	187.4701	41.67500	56.70519
At most 1	130.2850	150.5585	31.37333	50.59985
At most 2	98.91172	117.7082	25.11040	44.49720
At most 3	73.80132	88.80380	21.26893	38.33101
At most 4	52.53239	63.87610	17.56147	32.11832
At most 5	34.97092	42.91525	15.74699	25.82321
At most 6	19.22393	25.87211	11.02131	19.38704
At most 7	8.202622	12.51798	8.202622	12,51798
Panel B – USD				
*None**	225.3923	187.4701	58.74681	56.70519
*At most 1**	166.6454	150.5585	53.25196	50.59985
At most 2	113.3935	117.7082	29.30740	44.49720
At most 3	84.08608	88.80380	24.14897	38.33101
At most 4	59.93711	63.87610	22.28720	32.11832
At most 5	37.64992	42.91525	18.76806	25.82321
At most 6	18.88186	25.87211	11.38805	19.38704
At most 7	7.493808	12.51798	7.493808	12,51798
Panel C – CAD				
*None**	224.8096	187.4701	57.75380	56.70519
*At most 1**	167.0558	150.5585	52.61081	50.59985
At most 2	114.4450	117.7082	28.52831	44.49720
At most 3	85.91672	88.80380	26.77256	38.33101
At most 4	59.14416	63.87610	22.91941	32.11832
At most 5	36.22475	42.91525	17.82207	25.82321
At most 6	18.40268	25.87211	11.31315	19.38704
At most 7	7.089524	12.51798	7.089524	12,51798
Panel D – EUR				
*None**	225.4552	187.4701	60.23074	56.70519
*At most 1**	165.2244	150.5585	52.09463	50.59985
At most 2	113.1298	117.7082	30.23390	44.49720
At most 3	82.89591	88.80380	23.78698	38.33101
At most 4	59.10894	63.87610	22.53849	32.11832
At most 5	36.57045	42.91525	18.42171	25.82321
At most 6	18.14875	25.87211	10.93462	19.38704
At most 7	7.214124	12.51798	7.214124	12,51798
Panel E – HKD				
*None**	225.4270	187.4701	58.70932	56.70519
*At most 1**	166.7177	150.5585	53.36083	50.59985
At most 2	113.3569	117.7082	29.17679	44.49720
At most 3	84.18009	88.80380	24.18313	38.33101
At most 4	59.99696	63.87610	22.32361	32.11832
At most 5	37.67335	42.91525	18.69789	25.82321
At most 6	18.97545	25.87211	11.42907	19.38704
At most 7	7.546380	12.51798	7.546380	12,51798

the hypothesis of at most one cointegrating vector, indicating that there are exactly two cointegrating vectors present, this means that 8 markets are driven by 6 distinct stochastic trends. This result suggests a moderate but notable long-run integration across international equity markets when expressed in these common numeraires. It is worth mentioning that all of our conclusions are based on 5% significance level, the result would change when using a 10% significance level. Roughly speaking, higher significance level implies lower critical value, which means it is possible to get a higher rank result. In other words, if we choose a 10% significance level, some of the rank results could be 3 or higher.

Table. 6 Previous research results

Study	Markets analysed	Currency basis	Method / Notes	Cointegrating rank reported
Kasa (1992)	5 developed markets (US, Japan, UK, Germany, Canada)	Real USD (common numeraire)	Johansen VAR (monthly, 1974-1990)	r = 4
Richards (1995)	16 developed & emerging markets	Real USD	Johansen VAR (monthly, 1970-1992)	r = 0
DeFusco, Geppert & Tsetsekos (1996)	US, Korea, Philippines, Taiwan, Malaysia, Thailand	USD	Johansen VAR (1989-1995)	r = 0
Masih & Masih (1999)	United States, Japan, United Kingdom, Germany, Singapore, Malaysia, Hong Kong, and Thailand	Real USD	Johansen VAR (1992-1997)	r = 1 (7 trends remain)
Sharma & Wongbangpo (2002)	Indonesia, Malaysia, Singapore, Thailand and Philippines	Local currencies	Johansen VAR (monthly, 1986-1996)	r = 1 (Philippines excluded)
Click & Plummer (2005)	Indonesia, Malaysia, the Philippines, Singapore, and Thailand	Local & USD (both tested)	Johansen VAR (daily & weekly, 1998-2002)	Same r = 1 in both bases
Babaei, Hübner & Muller (2023)	G7 stock markets	USD (time-varying Kalman filter)	State-space cointegration (1990-2022)	Rank varies with uncertainty regime

Comparing our findings with earlier literature, the absence of cointegration in local-currency terms offers an insightful extension of Sharma and Wongbangpo's (2002) results. Their analysis of ASEAN markets identified a single cointegrating vector among Indonesia, Malaysia, Singapore, and Thailand, with the Philippine market isolated. Our broader and more recent sample underscores that the lack of integration in local currency terms extends globally, reinforcing the sensitivity of cointegration results to both sample periods and currency denominations.

Contrasted against our findings, Kasa (1992) reported four cointegrating vectors for five developed markets in real USD, implying a single common stochastic trend and suggesting tighter global integration during his study period. Our identification of two cointegrating vectors, hence six independent stochastic trends among eight markets, indicates weaker global integration than Kasa's findings, reflecting possibly the broader country mix and the period under study (2005-2025) that encompasses significant global financial disruptions such as the Global Financial Crisis and the COVID-19 pandemic. Meanwhile, Richards (1995) and DeFusco, Geppert, and Tsetsekos (1996), despite employing similar currency conversions, found no cointegration, emphasizing market segmentation during their study periods. Our contemporary findings indicate increased market integration over recent decades, potentially driven by intensified globalization, technological advancements, and expanded cross-border financial activities.

Babaei, Hübner, and Muller (2023) demonstrate that the existence and strength of cointegration among the G7 stock markets vary with shifts in global economic-policy and political uncertainty. Although their study does not include currency choice, such uncertainty often transmits through exchange-rate fluctuations, implicitly altering the cointegration structure that researchers observe. The fact that we detect no cointegration in local currencies yet consistently reveal two long-run vectors once the indices are expressed in a common numeraire aligns with this mechanism: policy-driven uncertainty, channelled via exchange-rate dynamics, can either mask or uncover the underlying equilibrium relationships across national equity markets.

In summary, our analysis confirms and enriches the existing body of literature by emphasizing the substantial influence currency denomination holds in assessing international equity market integration. Our results highlight the complex and conditional nature of long-run relationships among equity markets, emphasizing the necessity of considering currency effects carefully and advocating for a flexible, context-aware approach to understanding global financial integration.

5. Conclusion

This paper set out to answer a sharply focused question: Is the apparent cointegration of international stock markets robust to the currency in which those markets are measured? To isolate the role of denomination, we applied an identical Johansen specification to eight headline indices across five numeraires—local currency, USD, CAD, EUR, and HKD—over a period that spans three major crises: the 2008 global financial collapse, the 2011-12 euro-area turmoil, and the 2020-22 COVID-19 shock. The unified design ensures that any change in the inferred rank is attributable solely to the choice of numeraire, rather than to differences in lag length, deterministic terms, or sample window.

When prices are analysed in their domestic units, the trace and maximum-eigenvalue statistics both fail to reject the unit-root null at every rank; the eight markets therefore evolve along eight independent stochastic trends. This finding establishes a clean local-currency benchmark against which all subsequent conversions can be compared.

Expressing the same series in U.S., Canadian, Euro, or Hong Kong dollars alters that verdict consistently: each numeraire reveals exactly two cointegrating vectors. Although six distinct stochastic trends remain, the emergence of two equilibrium relationships indicates that currency translation exposes meaningful long-run linkages that local currency analyses obscure. This consistent outcome across multiple common numeraires highlights the robustness of cointegration patterns to currency conversion, though it still leaves substantial independent variation among these markets.

Because all numeraires are evaluated under an identical econometric design, the study demonstrates unequivocally that long-run market integration is sensitive to the unit of account. The evidence reconciles decades of inconsistent conclusions—ranging from complete segmentation to a single global trend—by showing that each position can be reproduced or eliminated simply by altering the currency basis.

Several limitations invite further enquiry and outline a structured agenda for future work. First, the present sample comprises eight large-capitalization benchmarks; extending the design to include mid-cap, frontier, or sector-specific indices would show whether numeraire sensitivity widens or narrows as one moves down the market-capitalization spectrum. Second, while the Johansen framework provides a clean static snapshot, rolling-window and state-space implementations could trace how cointegration ranks—and their currency dependence—shift through distinct monetary and geopolitical regimes. A natural extension is to embed exchange-rate uncertainty indices directly into a time-varying VECM so that rank changes can be attributed to identifiable policy shocks. Third, incorporating high-frequency data would clarify whether intraday currency co-movements propagate upward to the long-run linkages uncovered here. Finally, future work could rerun the analysis with gross and net total-return versions of each index—thereby incorporating dividends and withholding-tax conventions explicitly—to verify whether the cointegration ranks remain stable under alternative definitions of cash-flow reinvestment.

Looking beyond conventional research extensions, several structural shifts in the international monetary system may reshape the cointegration landscape documented here. First, the accelerating internationalization of the renminbi (RMB) suggests that a new, widely used numeraire could emerge.

Once a sufficiently long and continuous RMB-denominated price history becomes available for all sample markets, retesting under this currency will reveal whether the weak integration we observe in dollar-linked numeraires extends to a rising Asian reserve unit or produces a different pattern altogether. Second, the rollout of central-bank digital currencies (CBDCs) has the potential to tighten—or fragment—existing currency blocs in ways that conventional USD/CAD/EUR/HKD groupings cannot capture. Embedding CBDC adoption indicators or cross-border settlement data into a multi-currency VECM would permit real-time monitoring of whether digital settlement channels are more consistent with a common stochastic trend among equity markets, or the local-currency segmentation found in this study.

By situating our findings within these emerging monetary developments, future research can track the extent to which currency denomination remains a decisive factor gradually neutralize the numeraire effect identified here.

Despite these nuances, one conclusion remains unequivocal. Cointegration among international equity indices is not an inherent market property; it materialises only under specific measurement conventions. Consequently, any claim that global stock prices share a common long-run path must explicitly state—and persuasively defend—the numeraire that reveals such a path. Looking ahead, the most informative avenue will be research that combines multi-currency testing with time-varying econometric frameworks, allowing the cointegration rank itself to adjust as exchange-rate regimes, monetary conditions, and geopolitical landscapes evolve. Such work will clarify how these macro-financial forces jointly govern the long-horizon comovement of the world's equity markets.

Appendix. A

Source: LSEG Refinitiv

1. Histograms and statistics for FTSE

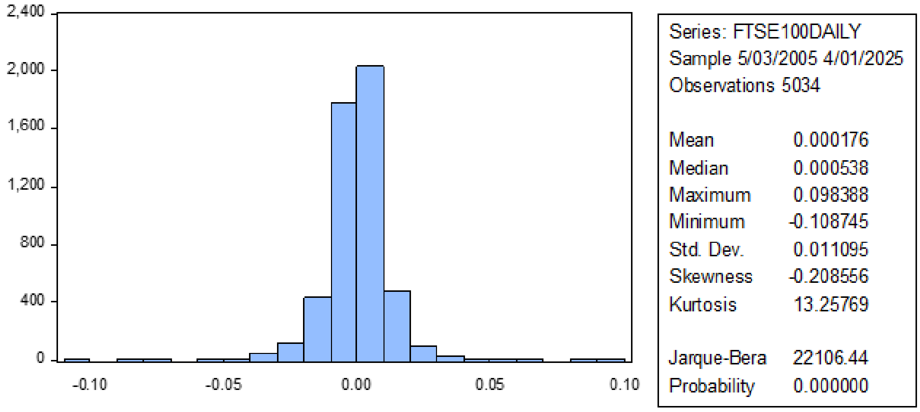


Figure. 1 Histogram and statistics of FTSE 100 (daily)

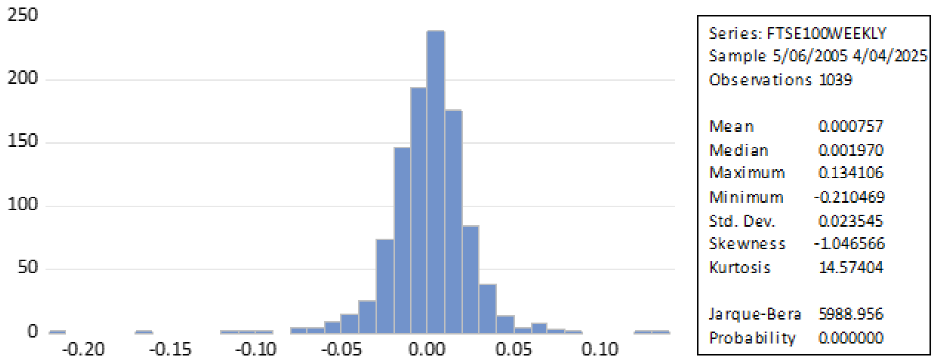


Figure. 2 Histogram and statistics of FTSE 100 (weekly)

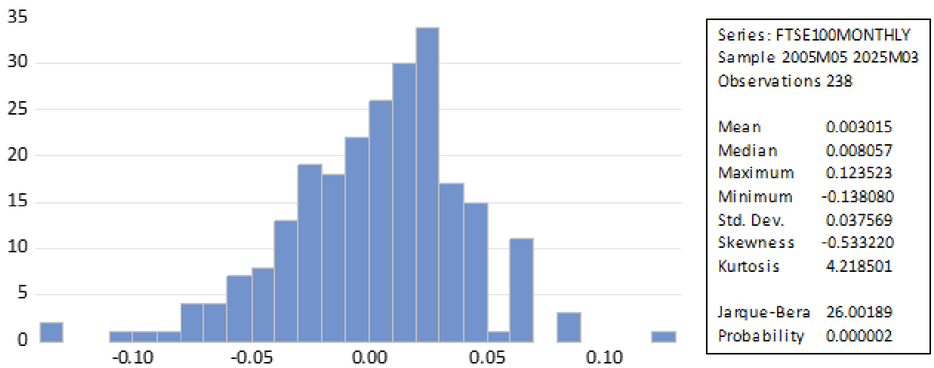
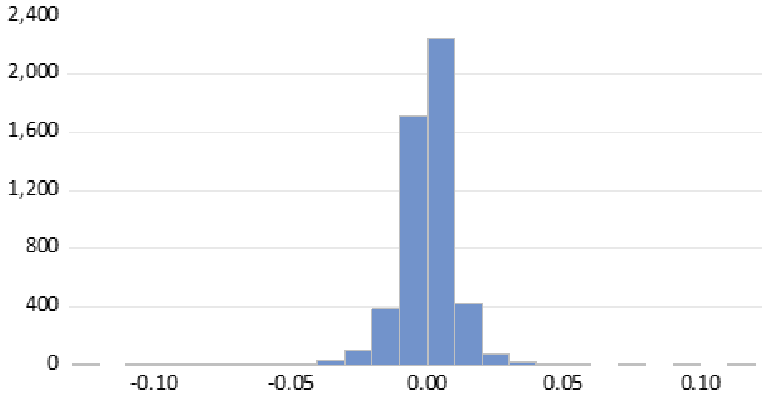


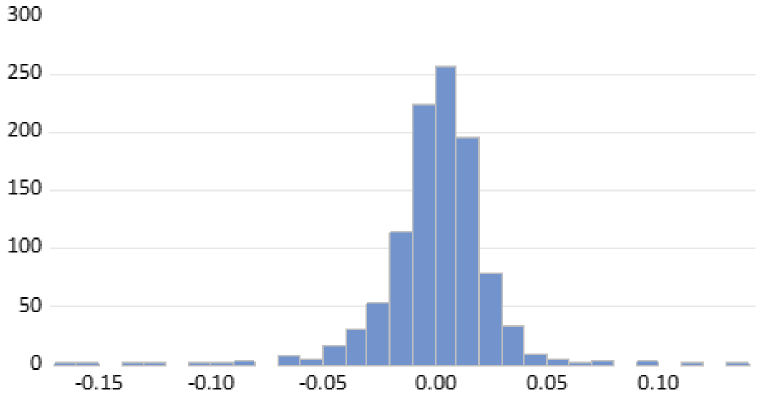
Figure. 3 Histogram and statistics of FTSE 100 (monthly)

2. Histograms and statistics for S&P/TSX



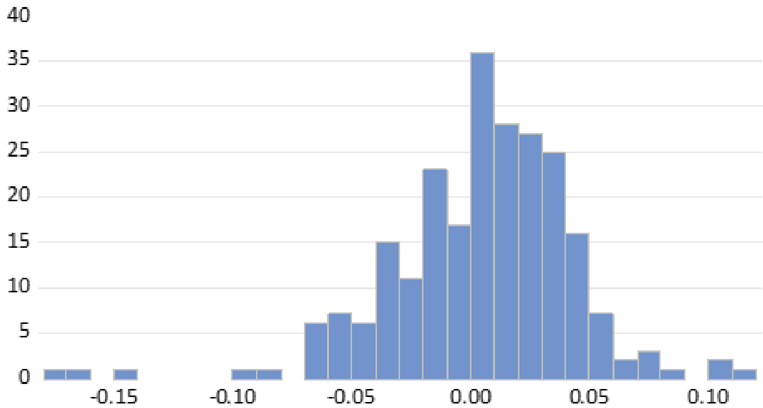
Series: TSXDAILY	
Sample 5/03/2005 4/01/2025	
Observations 4997	
Mean	0.000255
Median	0.000791
Maximum	0.119570
Minimum	-0.123450
Std. Dev.	0.010790
Skewness	-0.687454
Kurtosis	22.26349
Jarque-Bera	77655.98
Probability	0.000000

Figure. 4 Histogram and statistics of S&P/TSX (daily)



Series: TSXWEEKLY	
Sample 5/06/2005 4/04/2025	
Observations 1039	
Mean	0.001117
Median	0.003064
Maximum	0.136748
Minimum	-0.160894
Std. Dev.	0.022588
Skewness	-1.058642
Kurtosis	12.61665
Jarque-Bera	4197.686
Probability	0.000000

Figure. 5 Histogram and statistics of S&P/TSX (weekly)



Series: TSXMONTHLY	
Sample 2005M05 2025M03	
Observations 238	
Mean	0.004775
Median	0.008789
Maximum	0.112092
Minimum	-0.177353
Std. Dev.	0.038644
Skewness	-1.012571
Kurtosis	6.796202
Jarque-Bera	183.5808
Probability	0.000000

Figure. 6 Histogram and statistics of S&P/TSX (monthly)

3. Histograms and statistics for STI

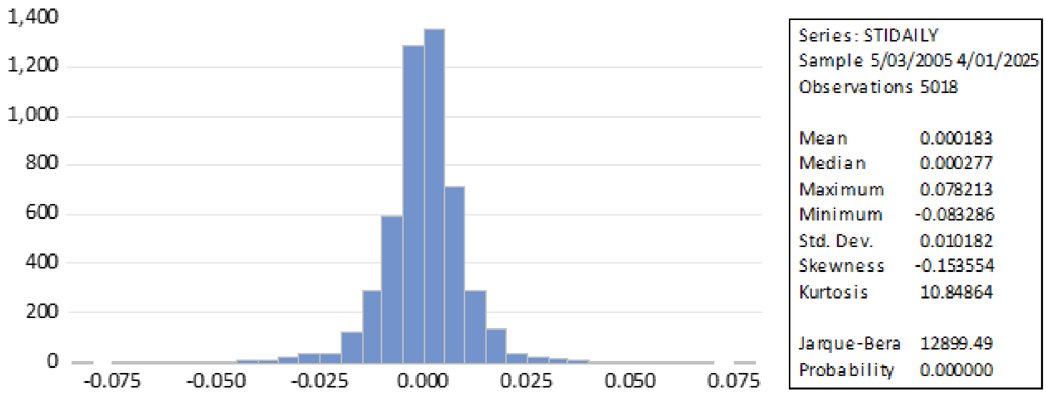


Figure. 7 Histogram and statistics of STI (daily)

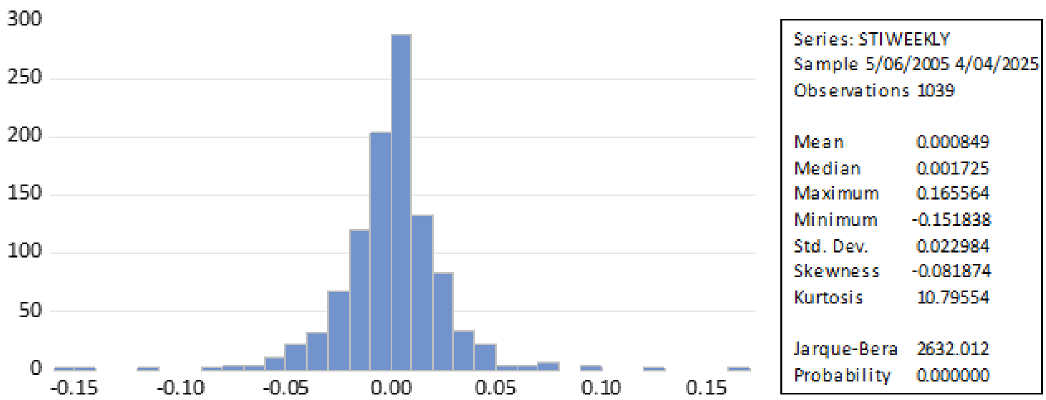


Figure. 8 Histogram and statistics of STI (weekly)

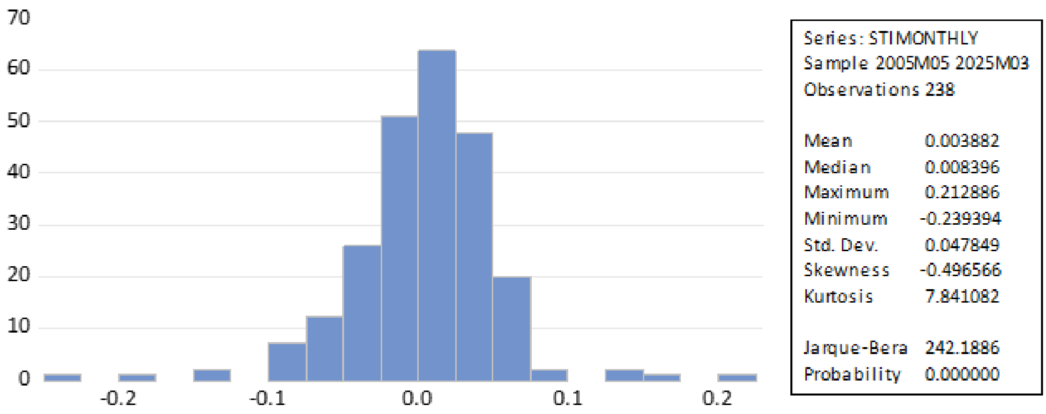


Figure. 9 Histogram and statistics of STI (monthly)

4. Histograms and statistics for Hang Seng

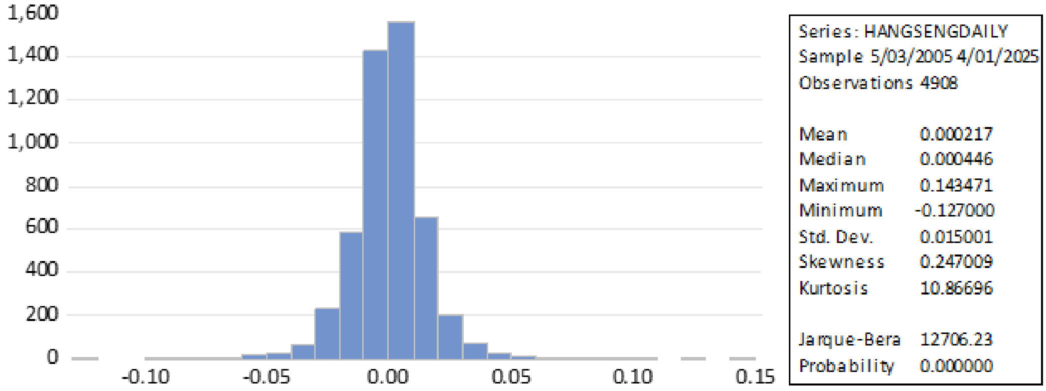


Figure. 10 Histogram and statistics of Hang Seng (daily)

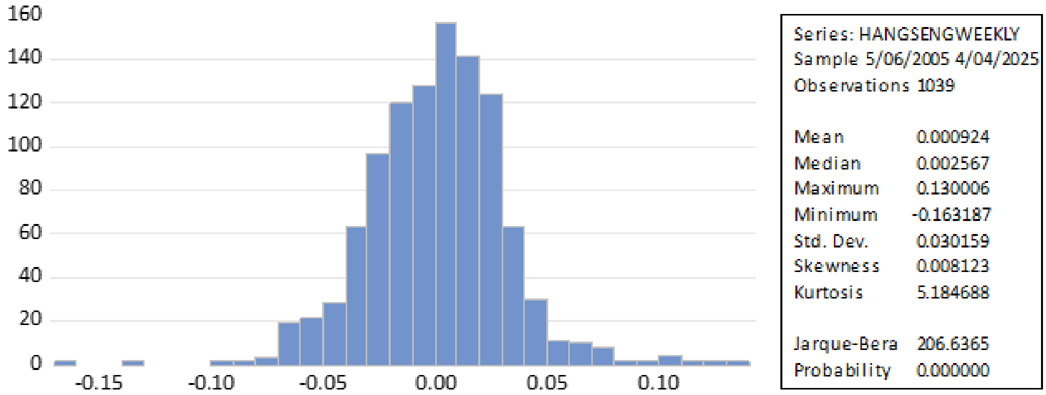


Figure. 11 Histogram and statistics of Hang Seng (weekly)

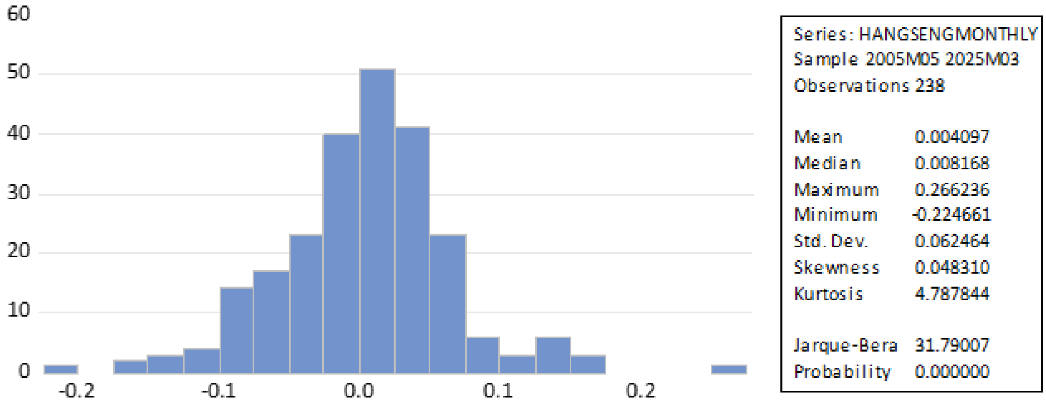


Figure. 12 Histogram and statistics of Hang Seng (monthly)

5. Histograms and statistics for DAX

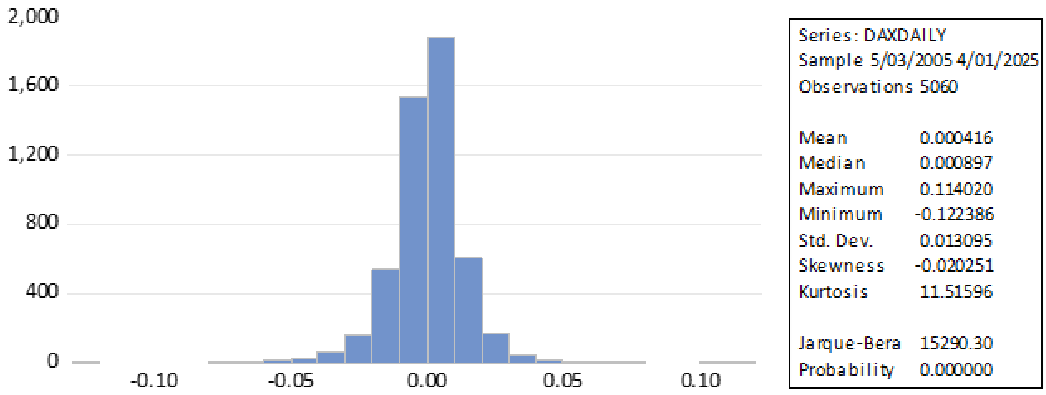


Figure. 13 Histogram and statistics of DAX (daily)

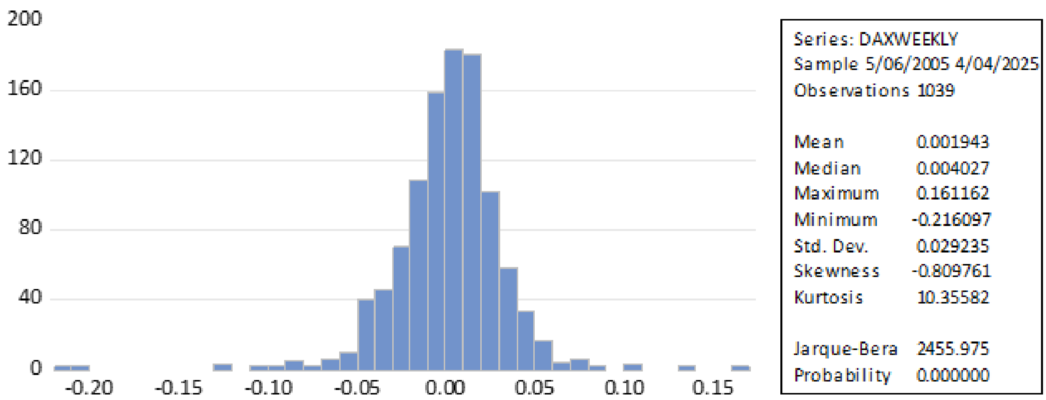


Figure. 14 Histogram and statistics of DAX (weekly)

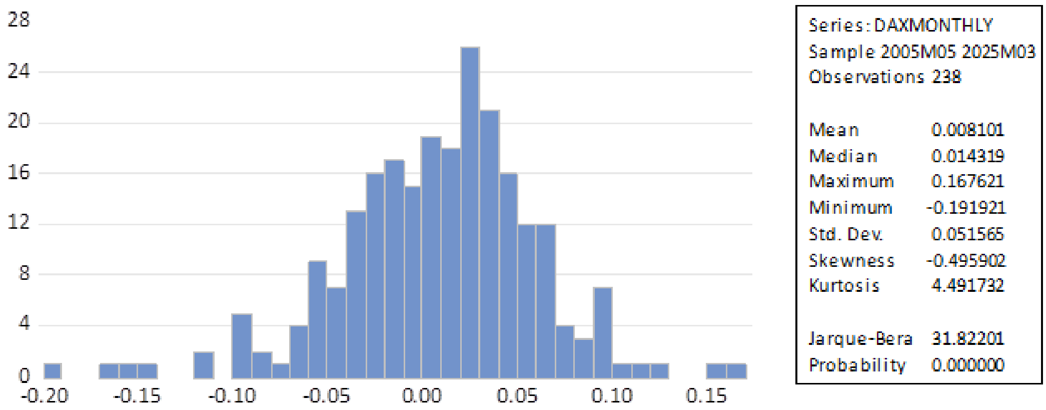


Figure. 15 Histogram and statistics of DAX (monthly)

6. Histograms and statistics for MIB

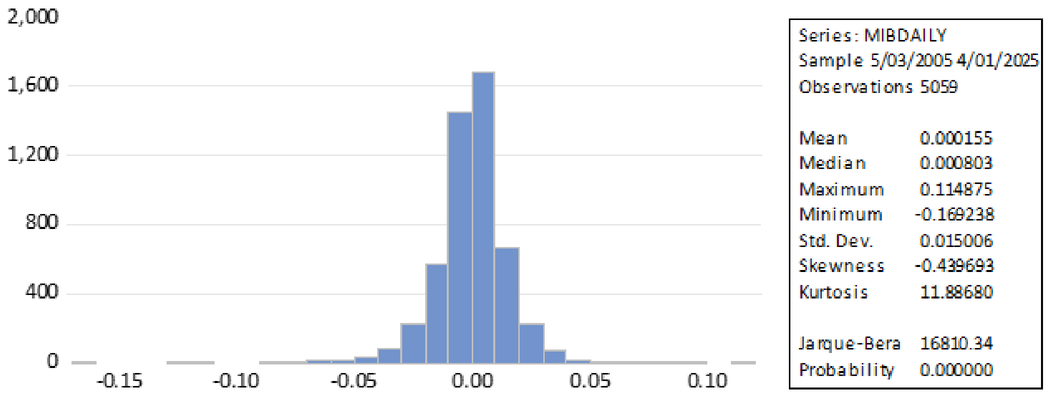


Figure. 16 Histogram and statistics of MIB (daily)

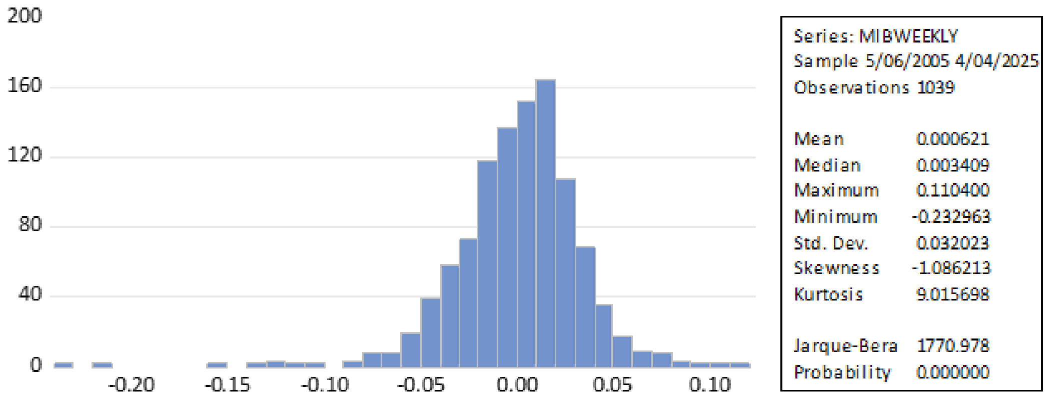


Figure. 17 Histogram and statistics of MIB (weekly)

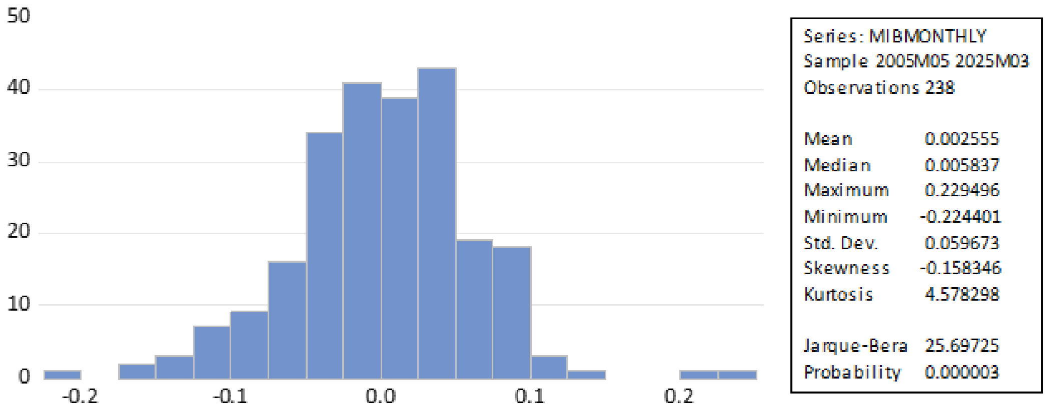


Figure. 18 Histogram and statistics of MIB (monthly)

7. Histograms and statistics for SSE

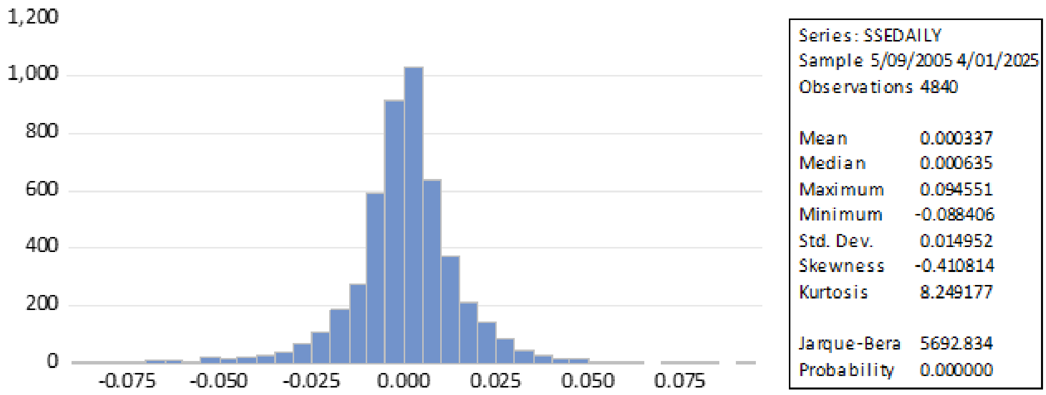


Figure. 19 Histogram and statistics of SSE (daily)

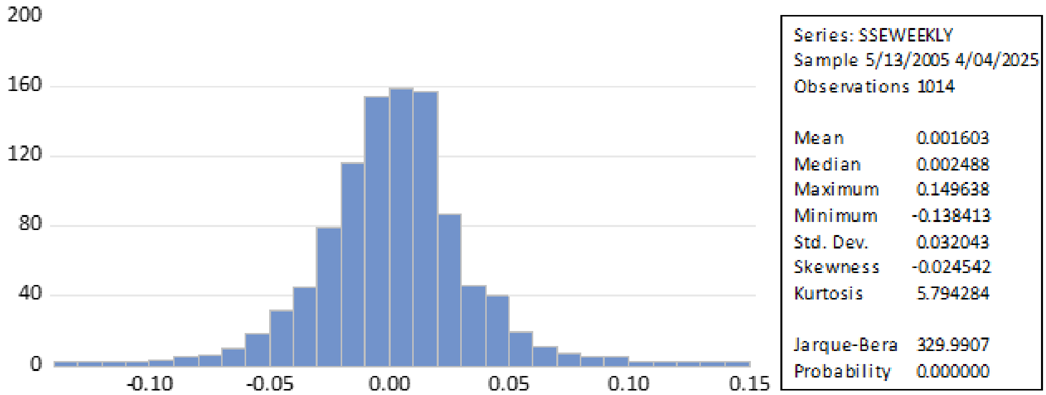


Figure. 20 Histogram and statistics of SSE (weekly)

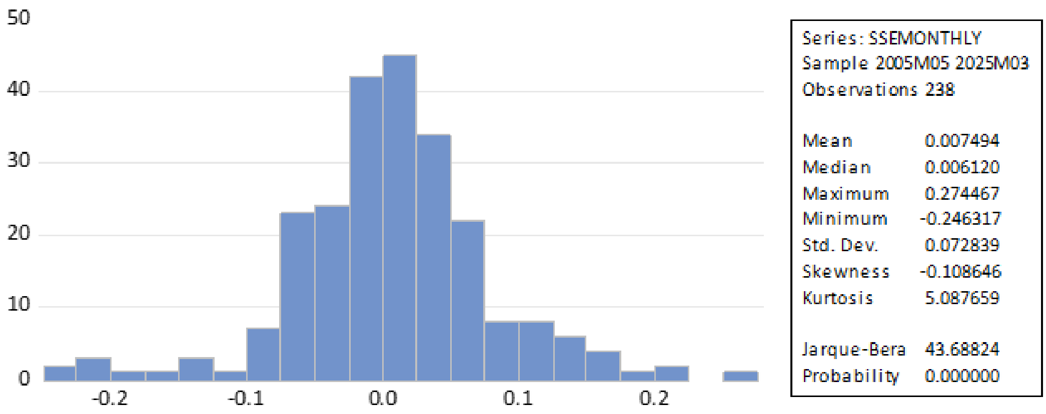


Figure. 21 Histogram and statistics of SSE (monthly)

Appendix. B

1. EViews Output for US dollar terms data

Johansen Cointegration Test

Date: 08/03/25 Time: 06:34
Sample (adjusted): 2005M10 2025M03
Included observations: 234 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: LNDAXUS LNFTSEUS LNHSUS LNMIBUS LNSP500 LNSSEUS LNSTIUS LNTSXUS
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.222020	225.3923	187.4701	0.0001
At most 1 *	0.203535	166.6454	150.5585	0.0044
At most 2	0.117720	113.3935	117.7082	0.0908
At most 3	0.098054	84.08608	88.80380	0.1044
At most 4	0.090849	59.93711	63.87610	0.1026
At most 5	0.077073	37.64992	42.91525	0.1523
At most 6	0.047502	18.88186	25.87211	0.2879
At most 7	0.031517	7.493808	12.51798	0.2958

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.222020	58.74681	56.70519	0.0309
At most 1 *	0.203535	53.25196	50.59985	0.0259
At most 2	0.117720	29.30740	44.49720	0.7362
At most 3	0.098054	24.14897	38.33101	0.7308
At most 4	0.090849	22.28720	32.11832	0.4713
At most 5	0.077073	18.76806	25.82321	0.3212
At most 6	0.047502	11.38805	19.38704	0.4741
At most 7	0.031517	7.493808	12.51798	0.2958

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

2. EViews Output for local currency data

Johansen Cointegration Test

Date: 08/03/25 Time: 06:46
Sample (adjusted): 2005M10 2025M03
Included observations: 234 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: LNDAX LNFTSE LNHS LNMIB LNSP500 LNSSE LNSTI LNTSX
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.163140	171.9601	187.4701	0.2317
At most 1	0.125475	130.2850	150.5585	0.3854
At most 2	0.101752	98.91172	117.7082	0.4124
At most 3	0.086884	73.80132	88.80380	0.3649
At most 4	0.072302	52.53239	63.87610	0.3085
At most 5	0.065080	34.97092	42.91525	0.2463
At most 6	0.046008	19.22393	25.87211	0.2677
At most 7	0.034447	8.202622	12.51798	0.2356

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.163140	41.67500	56.70519	0.6351
At most 1	0.125475	31.37333	50.59985	0.8917
At most 2	0.101752	25.11040	44.49720	0.9331
At most 3	0.086884	21.26893	38.33101	0.8935
At most 4	0.072302	17.56147	32.11832	0.8285
At most 5	0.065080	15.74699	25.82321	0.5673
At most 6	0.046008	11.02131	19.38704	0.5111
At most 7	0.034447	8.202622	12.51798	0.2356

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

3. EViews Output for Euro terms data

Johansen Cointegration Test

Date: 08/03/25 Time: 07:16
Sample (adjusted): 2005M10 2025M03
Included observations: 234 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: LNDAXEURO LNFTSEEURO LNHSEURO LNMIBEURO LNSP500EURO LNSPTSXEURO LNSSEEURO LNSTIEURO
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.226938	225.4552	187.4701	0.0001
At most 1 *	0.199586	165.2244	150.5585	0.0056
At most 2	0.121206	113.1298	117.7082	0.0940
At most 3	0.096658	82.89591	88.80380	0.1237
At most 4	0.091825	59.10894	63.87610	0.1180
At most 5	0.075706	36.57045	42.91525	0.1862
At most 6	0.045654	18.14875	25.87211	0.3340
At most 7	0.030359	7.214124	12.51798	0.3227

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.226938	60.23074	56.70519	0.0214
At most 1 *	0.199586	52.09463	50.59985	0.0346
At most 2	0.121206	30.23390	44.49720	0.6769
At most 3	0.096658	23.78698	38.33101	0.7549
At most 4	0.091825	22.53849	32.11832	0.4522
At most 5	0.075706	18.42171	25.82321	0.3458
At most 6	0.045654	10.93462	19.38704	0.5201
At most 7	0.030359	7.214124	12.51798	0.3227

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

4. EViews Output for CAD terms data

Johansen Cointegration Test

Date: 08/03/25 Time: 07:26
Sample (adjusted): 2005M10 2025M03
Included observations: 234 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: LNDAXCAD LNFTSECAD LNHSCAD LNMIBCAD LNSP500CAD LNSPTSXCAD LNSSECAD LNSTICAD
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.218712	224.8096	187.4701	0.0001
At most 1 *	0.201350	167.0558	150.5585	0.0041
At most 2	0.114777	114.4450	117.7082	0.0790
At most 3	0.108110	85.91672	88.80380	0.0793
At most 4	0.093302	59.14416	63.87610	0.1173
At most 5	0.073335	36.22475	42.91525	0.1982
At most 6	0.047197	18.40268	25.87211	0.3175
At most 7	0.029843	7.089524	12.51798	0.3353

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.218712	57.75380	56.70519	0.0391
At most 1 *	0.201350	52.61081	50.59985	0.0305
At most 2	0.114777	28.52831	44.49720	0.7828
At most 3	0.108110	26.77256	38.33101	0.5429
At most 4	0.093302	22.91941	32.11832	0.4240
At most 5	0.073335	17.82207	25.82321	0.3909
At most 6	0.047197	11.31315	19.38704	0.4816
At most 7	0.029843	7.089524	12.51798	0.3353

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

5. EViews Output for HKD terms data

Johansen Cointegration Test

Date: 08/03/25 Time: 07:05
Sample (adjusted): 2005M10 2025M03
Included observations: 234 after adjustments
Trend assumption: Linear deterministic trend (restricted)
Series: LNDAXHKD LNFTSEHKD LNHSHKD LNMIBHKD LNSP500HKD LNSPTSXHKD LNSSEHKD LNSTIHKD
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.221896	225.4270	187.4701	0.0001
At most 1 *	0.203906	166.7177	150.5585	0.0044
At most 2	0.117227	113.3569	117.7082	0.0913
At most 3	0.098186	84.18009	88.80380	0.1030
At most 4	0.090991	59.99696	63.87610	0.1015
At most 5	0.076796	37.67335	42.91525	0.1516
At most 6	0.047669	18.97545	25.87211	0.2822
At most 7	0.031735	7.546380	12.51798	0.2910

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.221896	58.70932	56.70519	0.0311
At most 1 *	0.203906	53.36083	50.59985	0.0252
At most 2	0.117227	29.17679	44.49720	0.7442
At most 3	0.098186	24.18313	38.33101	0.7285
At most 4	0.090991	22.32361	32.11832	0.4685
At most 5	0.076796	18.69789	25.82321	0.3260
At most 6	0.047669	11.42907	19.38704	0.4700
At most 7	0.031735	7.546380	12.51798	0.2910

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

References

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