ASEAN-6 Stock Markets' Long Memory Effect from 2006 to 2022: A Rescaled Range Analysis

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ABSTRACT

This paper provides new insights into market efficiency and fractal analysis in the ASEAN region by determining the presence of long memory, persistence, and nonperiodic cycles in the ASEAN-6 stock markets from 2006 to 2022. The ASEAN-6 stock markets' logarithmic daily returns are divided into different time periods namely: (1) pre-GFC to GFC, (2) post-GFC to Pre-COVID, and (3) COVID + U.S. inflationary periods. Assessment was done through the rescaled range analysis and Hurst exponent, bootstrap, and V-statistics. All ASEAN-6 markets exhibited long memory, showed trend persistency, exhibited nonperiodic cycles, and recorded Hurst exponents greater than 0.5 in all periods. Persistence was shown to be the highest during the pre-GFC to GFC, followed by the COVID-19 and U.S. inflationary, and then the post-GFC to pre-COVID. Vietnam had the highest persistence as evidenced by its Hurst coefficients. Thailand, Indonesia, and Malaysia had the lowest Hurst exponents, making them the best performers for each respective time period. Nonperiodic cycles were also observed for the entire time in each stock index. Results show clear evidence of market inefficiencies, especially during crises. By using this methodology, investors and financial institutions can become more aware of the unique investment risks of the ASEAN-6. This study could help investors mitigate some of the risks associated, especially during volatile economic periods and contribute to the existing literature by supporting policymakers in formulating strategies and regulations to strengthen the country's financial system, ensure transparency of financial information, and providing new insights into market efficiency.

Keywords: Long Memory, R/S Analysis, Hurst Exponent, V-statistics.

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1. INTRODUCTION

The paper analyzes long memory effects in the representative stock indices of ASEAN-6 countries namely Indonesia, the Philippines, Thailand, Malaysia, Singapore, and Vietnam. The focus is on different crisis periods from 2006 to 2022, including the 2008 Global Financial

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Crisis (GFC), the COVID-19 pandemic, and the 2022 U.S. Inflationary Period. These countries were selected due to their geographic proximity and similar economic performance.

The concept of long memory comes from the Fractal Market Hypothesis (FMH), that emerged as a response to the limitations of the Efficient Market Hypothesis (EMH). If the EMH assumes an "average prototypical rational investor," the FMH acknowledges diverse investor behaviors (Peters, 1994). In a fractal market, each time series retains past event as "memory," with recent events exerting a stronger influence (Metescu, 2022). This hypothesis better captures market behavior and requires extended time frames by incorporating long historical periods for reference.

Various stakeholders, including academics, investors, and analysts, have sought to understand market behavior during crises. showed the importance of financial knowledge in making sound investment decisions affecting market behavior in different asset classes (Abdullah *et al.*, 2020, as cited in Mandigma, 2023). The paper considered crises like the 2008 GFC and the COVID-19 pandemic, which had far-reaching economic consequences.

The study' aligns with the 8th (Decent Work & Economic Growth) and 17th (Partnership for the Goals) Sustainable Development Goals. It shows insights into ASEAN-6 stock market behavior and predictability, aiding investors, and portfolio managers during volatile economic times. The research findings can help minimize losses and contribute to market stability. Also, governments in ASEAN can use the study to identify market inefficiencies, which can inform regulatory improvements for economic and financial well-being.

2. LITERATURE REVIEW

2.1 Random Walk Hypothesis (RWH)

The theory states that stock prices follow an entirely random pattern since they are independent and uncorrelated from each other, making it impossible to forecast future prices and earn above-market returns (Rahman & Rahman, 2019). The random pattern was observed by Kayal and Mondal (2020) on the Nifty index and by Leone and Kwabi (2019) on the FTSE100 index.

Rahman and Rahman (2019) found that this theory was not observable at the Pakistani stock market due to the predictability of prices. The results indicated that random price movements do not always hold for all indices and component stocks across varying time frames (Kayal & Mondal, 2020; Leone & Kwabi, 2019; Rahman & Rahman, 2019).

2.2 Efficient Market Hypothesis (EMH)

The EMH is based on a more enhanced framework related to RWH, suggesting that an efficient market is when all information is immediately expressed in the stock prices and that they are following a random walk (Boya, 2019; Wong, 2020). There were studies that had both supported and challenged EMH. Boya (2019) concluded inefficiency in the French stock market during domestic and global crises. Then, Lamouchi (2020) found increased volatility due to Saudi Arabia's first stock market collapse and the decline in oil prices. Another study showed that EMH does not necessarily hold in markets filled with risk-averse traders, even under market efficiency (Chudik *et al.*, 2010, as cited in Patil *et al.*, 2017).

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According to Choi (2021), multifractality and persistence were displayed during the COVID-19 pandemic, contrasting the result for GFC. The mentioned study discerned varying results of efficiency on specific financial markets, and macroeconomic events can influence the behavior of stock returns, leading to multifractality and long memory. It indicated a meaningful repercussion on the EMH, paving the way for the underlying principles of FMH.

2.3 Chaos Theory

Based on the critics of RWH and EMH, these hypotheses do not account for the behavior of financial markets during times of chaos (Albulescu *et al*., 2021). Chaos theory pertains to a dynamic system where small changes in its initial form have tremendous consequences or impact on the long-term scale (Hanias *et al*., 2020; Jóźwiak *et al*., 2020). Anca-Iuliana (2018) concluded that indicators like consumption per capita and real GDP are persistent and can be analyzed using the time series approaches provided.

Mota and Crispim (2022) utilized this for an automobile original equipment manufacturer to identify early warning signs, improve decision-making systems, and monitor how employees handle disruptions from various crises. This study showcased that chaos theory can be applied at mathematical, risk management, economic, and business levels. These imply that small changes can have significant effects in a time series.

2.4 Fractal Market Hypothesis (FMH)

According to FMH, each observation "carries" a recollection of all previous occurrences. In essence, what happens now affects the future, and what took place in the past affects what is occurring now (Metescu, 2022). Multiple studies explored this theory on chosen stock markets, such as Faurani et al. (2019) found persistence and long-term memory for the ASEAN-5 countries' stock indices, while Miloş *et al*. (2020) rejected the EMH in seven European countries, revealing multifractality and fluctuations.

Okorie and Lin (2021) studied fractal contagions in 32 stock markets during COVID-19. Multifractal effects were mentioned in the studies of Aslam *et al*. (2020) during the pandemic on European stock indices, Gaio *et al*. (2022) on six countries during the Russia-Ukraine war, and Han *et al*. (2019) on five chosen Chinese stock markets.

2.5 Rescaled Range (R/S) Analysis

One of the powerful methods in calculating the Hurst exponent, which is related to long memory and (fractional) Brownian motion, is the R/S analysis (Gomes *et al*., 2018). Using this test, Bala and Gupta (2019) found persistent behavior in Indian stock market returns, Caporale *et al*. (2022) concluded that the traditional and ESG stock indices from different countries did not differ regarding persistence, and Bhattacharya *et al*. (2018) deduced that there were no significant differences in returns between the chosen stock. Xu (2022) assessed that the market indices of the BRICS countries exhibited long memory. R/S analysis has proven to be an effective method in identifying long memory within markets as characterized by the Hurst exponent.

3. FRAMEWORK OF THE STUDY

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3.1 Theoretical Framework

The RWH was coined by Bachelier in 1900 after observing that historical prices contain useless information (Rahman & Rahman, 2019). It stated how public or internal information cannot be used by investors to implement investment strategies and give supernormal returns because prices follow a random walk (Ananzeh, 2016; Kiyilar, 1997, as cited in Erdas, 2019). It also had no memory, which means one cannot predict future prices using historical prices.

The EMH introduced by Fama in 1970 stated that financial markets are considered "informationally efficient" if recent public information is immediately adjusted to the prices, preventing investors from constantly beating the market average (Blackledge & Lamphiere, 2021). This means that as the market randomly receives new information, movements in asset prices should also follow. As a result, it prevents any opportunities for price prediction since increased market efficiency results in increased randomness of price fluctuations.

Chaos theory was discovered by Lorenz while attempting to predict weather conditions he found that events were significantly affected by a tiny difference in conditions (Bulusu *et al*., 2020). Chaos analysis has already determined that market prices by the minute will resemble the shape of prices reflecting several years (Biswas *et al*., 2018).

Peters (1994) redefined what it means to have a stable market through FMH. He argued that when there is a threat to liquidity, an investor would be forced to cash out the investment no matter the current price, as explained through supply and demand. This then implies that when the market is liquid, then the prices are "close to fair", and thus, there is stability.

3.2 Operational Framework

The operational framework of this paper is divided into two phases and follows a downward process with the aim of detecting the long memory effect and persistence of ASEAN-5 stock markets.

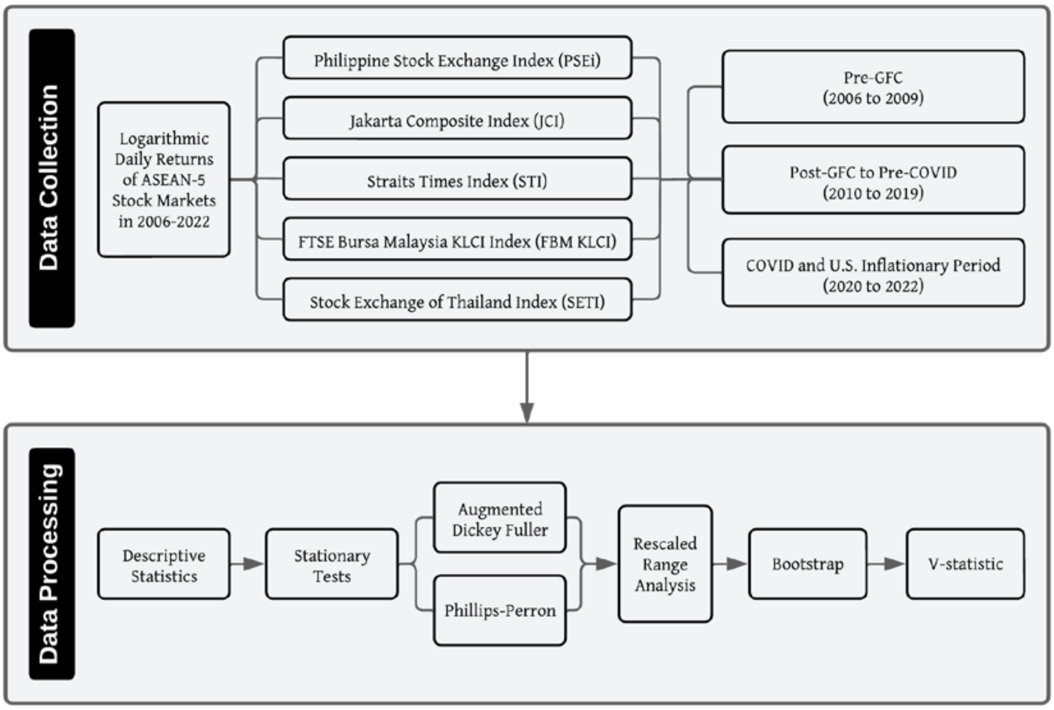

Figure 1. Operational Framework

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4. METHODOLOGY

4.1 Research Design and Method of Data Collection

Descriptive and causal-comparative research design examined the ASEAN-6 stock market behavior and movements during various crisis periods in terms of persistence, periodicity, and long memory effect. The paper used the logarithmic daily returns of FBM KLCI, JCI, PSEI, SETI, STI, and VNI retrieved from Refinitiv Eikon. The data ran from January 1, 2006 to December 31, 2009 for the pre-GFC to the GFC, January 1, 2010 to December 31, 2019 for the post-GFC to the pre-COVID, and January 1, 2020 to December 31, 2022 for the COVID + U.S. inflationary period.

4.2 Method of Data Analysis

The mean, min-max values, and standard deviation were calculated as part of the study's descriptive statistics as shown below in Table 1. Unit root tests, like the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP), were then performed so that bias could be avoided from the presence of non-stationary data (Dittrich & Srbek, 2020). After confirming the data's stationarity for each period, the study employed the R/S analysis while incorporating the bootstrap method to derive the Hurst exponents and V-statistic plots to detect long memory and cycles.

Table 1. Descriptive Statistics

Country	Mean	Min	Max	SD
Pre-GFC Period (2006 - 2009)				
Indonesia	0.0010	-0.1038	0.0792	0.1798
Malaysia	0.0004	-0.0950	0.0435	0.0099
Philippines	0.0005	-0.1227	0.0982	0.0164
Singapore	0.0004	-0.0833	0.0782	0.0160
Thailand	0.0002	-0.1484	0.1116	0.0166
Vietnam	0.0007	-0.0888	0.0476	0.0209
Post-GFC Period (2010 - 2019)				
Indonesia	0.0004	-0.0888	0.0727	0.0104
Malaysia	0.0001	-0.0318	0.0338	0.0057
Philippines	0.0004	-0.0675	0.0570	0.0105
Singapore	0.0001	-0.0430	0.0334	0.0078
Thailand	0.0004	-0.0565	0.0592	0.0095
Vietnam	0.0003	-0.0587	0.0450	0.0111
COVID + Inflationary (2020 - 2022)				
Indonesia	0.0002	-0.0658	0.1019	0.0119
Malaysia	0.0000	-0.0536	0.0685	0.0093
Philippines	-0.0001	-0.1334	0.0744	0.0157

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Singapore	0.0001	-0.0735	0.0607	0.0104
Thailand	0.0002	-0.1080	0.0795	0.0124
Vietnam	0.0002	-0.0667	0.0498	0.0145

Through the application of R/S analysis, the Hurst exponent was derived to establish the existence of long0.0982 memory and if a time series is time-dependent or follows a random walk (Lin *et al*., 2021). The steps for conducting the R/S analysis were:

Step 1. The time series of the returns of a stock index P_t was transformed into log returns denoted as R_t, through the equation

$$R_t = loglog\left(\frac{P_t}{P_{t-1}}\right) = logP_t - logP_{t-1} \quad (1)$$

Step 2. The R/S displays partial sums of variances in a series of returns, scaled by volatility. Its average return R was also computed using R_t. Thus, the R/S statistic was obtained through

$$\underline{Q}_n = \frac{1}{s_n}\left[\max \sum_{j=1}^{k}\left(R_j - \underline{R}\right) - \min \sum_{j=1}^{k}\left(R_j - \underline{R}\right)\right] \quad (2)$$

that follows the notation used by Lo (1991, as cited in Zheng *et al*., 2018). It should be noted that the scaling was done using the maximum likelihood estimator of the standard deviation

$$s_n = \left[\frac{1}{n}\sum_{j=1}^{k}\left(R_j - \underline{R}\right)^2\right]^{1/2} \quad (3)$$

Finally, Hurst's exponent, H , as mentioned by Caporale *et al*. (2022) and Rajagopal (2018), can be categorized into three: (1) H = 0.50 pertains to a classical Brownian motion or random series with uncorrelated returns and no presence of long or short memory; (2) 0.50 < H ≤ 1 signifies a persistent behavior, positively correlated returns, and long-range dependence; or (3) 0 ≤ H < 0.50 denotes an anti-persistent behavior, negatively correlated returns, and short-range dependence.

Davies and Harte (1987, as cited in Zheng *et al*., 2018) and Lo (1991, as cited in Zheng *et al*., 2018) pointed out that the R/S analysis requires long periods to detect persistence and improve the results' reliability, but it would still be possible to make inferences using bootstrap. Politis and Romano (1994, as cited in Kang *et al*., 2021) recommended stationary bootstrapping - a tool used to generate bootstrap resamples of a random block length that follows a geometric distribution in stationary data. Using a stationary time series R_t, the resamples generated by the stationary bootstrap are composed of Q random blocks of the original time series given by

$$R_b^* = \left\{R_{T_1}, R_{T_2}, \ldots, R_{T_Q}\right\} \quad (4)$$

This resampled time series from bootstrapping becomes the basis for calculating the Hurst exponent H_b, and generates a set of estimates $\{H_1, H_2, \ldots, H_B\}$.

Finally, the V-statistic is an equation by Hurst (1956, as cited in Celeste *et al*., 2020) used to find out whether there is a cycle in the time series or not, and how long this cycle is:

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$$V_n = \frac{(R/S)_n}{\sqrt{n}} \tag{5}$$

The plot that was generated by the V-statistic would show a rising or falling cycle, wherein it would have an upward slope if H > 0.5 and a downward slope if H < 0.5. The flattened parts would signify the end of the cycle (Celeste *et al*., 2020).

5. RESULTS AND DISCUSSIONS

Hurst Exponents & Trend Persistence

Table 2. Hurst coefficients & Bootstrap results of ASEAN-6 in each time period

Country	Hurst	Bootstrap Results		
		S. Dev	95% Lower	95% Upper
Pre-GFC to GFC Period (2006 to 2009)				
Indonesia	**0.5965**	0.0239	0.5638	0.6587
Malaysia	**0.6129**	0.0280	0.5553	0.6709
Philippines	**0.5829**	0.0296	0.5419	0.6535
Singapore	**0.6007**	0.0272	0.5600	0.6659
Thailand	**0.5734**	0.0288	0.5317	0.6453
Vietnam	**0.6493**	0.0247	0.5959	0.6936
Post-GFC to Pre-COVID Period (2010 to 2019)				
Indonesia	**0.4881**	0.0250	**0.5029**	**0.5940**
Malaysia	**0.5192**	0.0263	0.5099	0.6098
Philippines	**0.5312**	0.0256	0.5122	0.6103
Singapore	**0.4833**	0.0239	**0.5138**	**0.6097**
Thailand	**0.5400**	0.0242	0.5318	0.6188
Vietnam	**0.5559**	0.0255	0.5259	0.6217
COVID and U.S. Inflationary Period (2020 to 2022)				
Indonesia	**0.5830**	0.0283	0.5489	0.6535
Malaysia	**0.5485**	0.0313	0.5153	0.6418
Philippines	**0.5488**	0.0317	0.5108	0.6392
Singapore	**0.5588**	0.0291	0.5379	0.6449
Thailand	**0.5580**	0.0287	0.5364	0.6410
Vietnam	**0.6064**	0.0278	0.5617	0.6708

Note. Hurst values in red fonts indicate that it is more than the required threshold (H > 0.5). Indonesia and Singapore's values are in green font because H stayed below 0.5, which is why the bootstrap results were also given emphasis.

JCI (Indonesia)	FBM KCLI (Malaysia)	PSEi (The Philippines)
		
STI (Singapore)	SETI (Thailand)	VNI (Vietnam)

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Figure 2. Trend Persistence of each ASEAN-6 stock market

Figure 2 and Table 2 above showcased the estimated Hurst coefficients after the application of the R/S analysis. Markets that achieved a Hurst value greater than 0.50 but less than or equal to 1 ($0.50 < H \leq 1$) are considered persistent and inefficient.

JCI was shown to have a persistent upward trend over time. It had a high Hurst coefficient during the pre-GFC to GFC and COVID + U.S. inflationary periods, valuing at H=0.5965 and H=0.5830, respectively. Although it did not break the H=0.5 threshold during the post-GFC to pre-COVID (2010-2019) period as its Hurst coefficient was only equal to 0.4881, the researchers still arrived at the same conclusion. This is because the bootstrap results ranged from H=0.5029 to H=0.5940.

The Malaysian stock market also generally exhibited a positive upward trend and had Hurst exponents higher than 0.5, indicating persistency and inefficiency. A sharp decline in stock prices could be observed due to the GFC and was even observed to be the lowest in the years 2006 to 2022. The FBM KLCI started to recover from the effects of GFC at the start of 2010 until about 2019. After recovering from the GFC, stock prices fell once again from the start of 2020 until the end of 2022 due to the COVID-19 pandemic.

The R/S analysis also confirmed that the Philippine stock market exhibited long memory effects during all periods, with all its Hurst exponents exceeding 0.5, although lower than its other ASEAN-6 peers. A persistent downtrend can be observed during the pre-GFC to GFC from 2007 to 2009, that was followed by a persistent uptrend during the post-GFC to pre-COVID period from 2010 to 2019 and a persistent downtrend during the COVID period in 2020.

As for the Singaporean stock market, STI generally showed persistent behavior and positive upward trend from 2006 to 2022. During the pre-GFC to the GFC period and the COVID and U.S. inflationary period, H values were computed to be 0.6007 and 0.5588 respectively which showed that Singapore exhibited long memory. Although the STI had an H value of 0.4833 during the post-GFC period, the bootstrap values ranged from 0.5138 to 0.6097, which indicated that there was an outlier in the dataset that caused the H value to drop. In essence, since the lower 95% bootstrap had a value of 0.5138, this signified that the Singapore stock market still exhibited signs of persistence and long memory.

Following the other stock markets, the plot in Figure 2 showcased that the Thailand Stock Market had a general persistent trend and a consistent Hurst value greater than 0.5. Visible declines were displayed in the daily stock prices from 2008 to 2009 and from 2020 to 2021, that were the periods of the GFC and the COVID-19 pandemic. Thailand’s stock market then exhibited significant long memory, persistence, and inefficiency.

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Across the six countries, Vietnam recorded the highest Hurst coefficients in all periods of interest. It had a value of H=0.6493 during pre-GFC to GFC, H=0.5559 during post-GFC to pre-COVID, and H=0.6064 during the COVID-19 + U.S. inflationary period. Among the ASEAN-6, VNI exhibited long memory the most in the years 2006 to 2022.

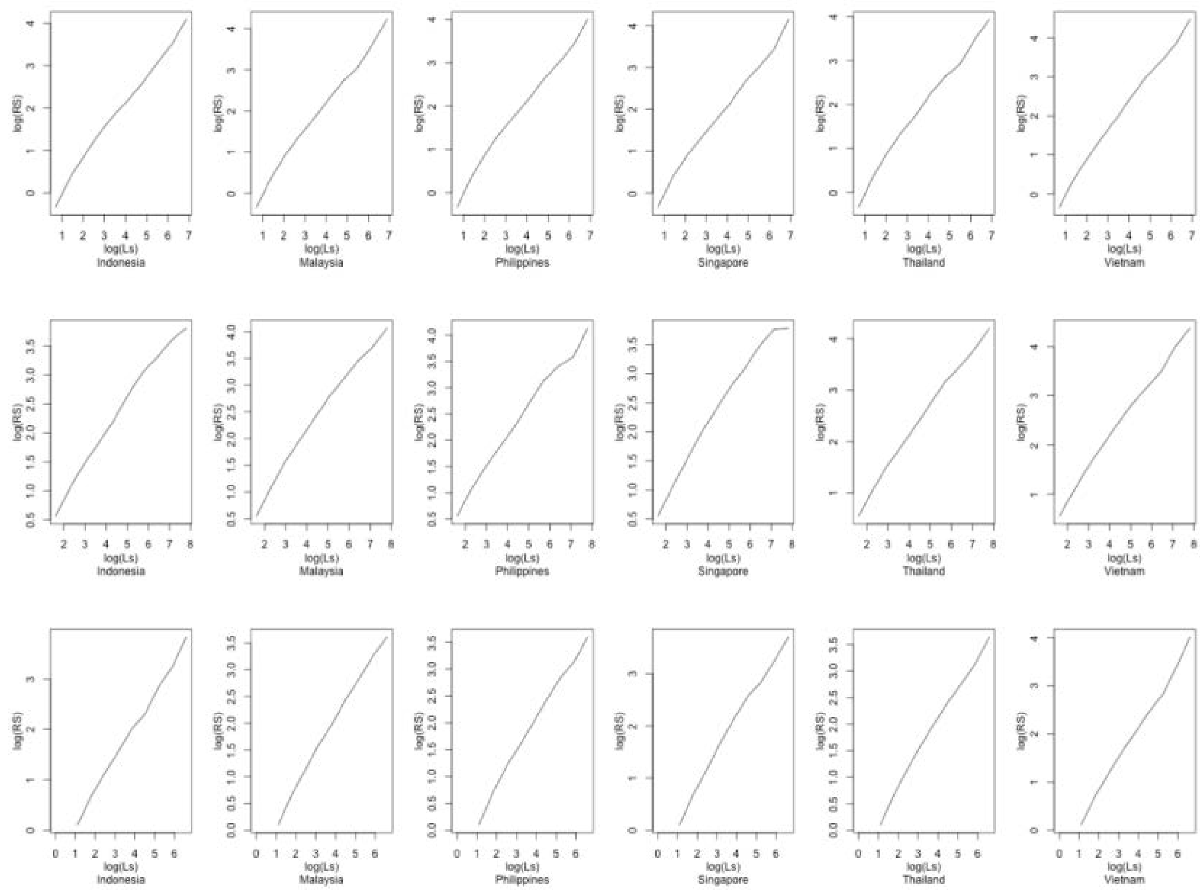

Figure 3. V-Statistics for Country Indices. From top to bottom: Pre-GFC to GFC, Post-GFC to Pre-COVID, COVID-19 and Inflationary Period

Figure 3 shows the V-statistics plots used to identify nonperiodic cycles. A rising slope indicates the existence and continuity of a cycle. In a series with only one nonperiodic cycle, this trend would not be broken. When the trend is broken, there will be a noticeable inflection point that will either look like a flat line or a complete change to a downward direction. The number of inflection points represents an estimate of the number of nonperiodic cycles that are present in the series.

An overall upward direction was present for Indonesia in the pre-GFC to GFC period. The first inflection point was estimated to be in August 2011. This was followed by the next break during the COVID and U.S. inflationary period, where the trend halted at around March 2020.

As for Malaysia, there was a break in the positive slope around each period, which was estimated to be around August 2006 and August 2007 for pre-GFC to GFC, August 2010 for post-GFC to pre-COVID, and August 2021 for the COVID + U.S. inflationary period.

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There were no evident inflection points in the Philippine stock market during the pre-GFC to GFC period. This represented one big cycle that continued until the post-GFC to the pre-COVID that was broken approximately in December 2010. During the COVID + U.S. inflationary, the positive slope was broken off in August 2020.

Similarly, Singapore experienced no breaks for the pre-GFC to GFC period. As for the post-GFC to the pre-COVID period, there was an inflection point in August 2010 indicating that the nonperiodic cycle was broken off. Meanwhile, in the COVID + U.S. inflationary period, the inflection point happened around March 2020.

For the Thai stock market, there was a positive slope during the pre-GFC to GFC period. However, there was a break in the upward trend during May 2006. In terms of the post-GFC to pre-COVID, there was also an increasing trend in the Thailand stock market that was broken off in December 2010. There were no breaks recognized during the COVID + U.S. inflationary.

Finally, VNI demonstrated nonperiodic cycles during each period and had an inflection point in both the post-GFC to pre-COVID and COVID-19 and U.S. inflationary periods. These were estimated to be around August 2010 and May 2020, respectively.

Table 3. Summary of Hurst coefficient, Persistence, and presence of Nonperiodic cycles

	Hurst Value	Trend Persistence			Nonperiodic Cycle
Indonesia	H > 0.5	↓	↑	↓	All periods
Malaysia	H > 0.5	↓	↑	↓	All periods
Philippines	H > 0.5	↓	↑	↓	All periods
Singapore	H > 0.5	↓	↑	↓	All periods
Thailand	H > 0.5	↓	↑	↓	All periods
Vietnam	H > 0.5	↓	↑	↑	All periods

6. CONCLUSIONS AND RECOMMENDATIONS

The results showed that all ASEAN-6 stock markets had Hurst exponents of greater than 0.5 in all periods, that were more in line with the FMH than the RWH and EMH, showing more than a 50% probability that the stock price will continue to trend in the same direction in the succeeding period. On a per period basis, the highest Hurst exponents were recorded during the pre-GFC to GFC, followed by the COVID + U.S. inflationary, and the post-GFC to pre-COVID.

The existing literature attributed the inefficiencies in ASEAN-6 stock markets to economic and financial market uncertainties brought about by the global crises (Miloş, 2020). Vietnam had the highest Hurst exponents in all periods, suggesting that it displayed the most prominent long memory effect, persistence, inefficiency, and predictability. Opposite of this were Thailand, Indonesia, and Malaysia, which had the lowest Hurst exponents during each respective period. Since these are ranked the lowest, the researchers conclude that they are also the countries that performed relatively best during the specific period of interest.

Finally, all ASEAN-6 were concluded to have experienced nonperiodic cycles during 2006-2022. Particularly, Indonesia, Philippines, Singapore, and Vietnam showed no breaks in the pre-GFC to GFC period, which signified that these countries were experiencing one big cycle until the first inflection point in the succeeding period.

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Sophisticated investment funds like hedge funds use similar long memory strategies like using long memory principles to identify market trends and manage risks by using algorithms, machine learning and complex finance models. Investors who understood the effects of long memory on equity markets on persistent volatility especially during the global financial crises to mitigate risks would reduce their market exposure or use hedging strategies to cut their losses by investing in negatively correlated assets.

R/S analysis, through Hurst exponent and V-statistic, is focused on testing for market efficiency or inefficiency by identifying persistence and detecting cycles. Since the findings in this study demonstrated that market inefficiencies could arise in stock markets, that become stronger during periods of crises, this means that some stocks could exhibit persistence and not trade in their fair values. The conclusion that can be made with the help of this methodology serve as evidence that there is a degree of predictability in markets.

Long memory models can be used by investors to predict periods of high volatility like to global financial crisis and the high inflationary period by anticipating these periods and used these opportunities to identify persistent downward or upward trends during periods of uncertainty and changing market conditions to mitigate their losses by adjusting their portfolios based on real time data. These persistent downward or upward trends during high volatility periods could signal buying or selling opportunities for the investors.

The study then gives the opportunity for investors to beat the market average by predicting trends, while preventing potential losses. When the Hurst value is more than 0.5, it shows strong persistence which investors and portfolio managers can use alongside indicators used in technical analysis to predict potential uptrends or price reversals in the market. An investor, for example, may look for stocks with H values greater than 0.5 whose prices have been in an uptrend, or H values less than 0.5 whose prices have been decreasing for some time to time their investment.

For future studies, researchers may further explore by reviewing concepts not discussed in the study. They may incorporate alternative techniques such as the modified R/S analysis and the detrended fluctuation analysis, to compare & contrast and provide significant insights. Also, researchers may assess other foreign countries and oversee other corresponding markets, such as sectorial indices, foreign exchanges, or bond markets, depending on the available data. They may also focus on different financial crises or events to investigate its impact. This research adds to the body of literature by helping investors and financial institutions mitigate market risks during volatile periods and improving their profitability in trading portfolios thus encouraging further market development of equities markets.

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