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HURST EXPONENT AS A REGIME-SWITCHING INDICATOR FOR TREND-FOLLOWING STRATEGIES IN EAST ASIAN STOCK MARKETS

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Abstract. This study evaluates the Hurst exponent as a regime-switching indicator for trend-following strategies across five major East Asian stock indices: the SSE, N225, HSI, TAIEX, and KOSPI. We quantify market persistence using two established estimators, rescaled range (R/S) analysis and detrended fluctuation analysis (DFA), and test the performance of four distinct strategies—*buy-and-hold*, *long-only*, *short-only*, and a *combined long-short* system—using signals from a 10-day exponential moving average (EMA10). Our results reveal a strong relationship between persistence and strategy performance: periods with high Hurst values yield superior returns under the combined long-short strategy, with DFA proving the more robust estimator for detecting trending regimes. Conversely, during anti-persistent phases (low Hurst values), the buy-and-hold approach dominates. These findings provide empirical evidence that the Hurst exponent can serve as a practical tool for dynamic strategy selection, enabling traders to align their approach with prevailing market conditions.

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Key words and phrases. Hurst exponent; regime switching; trend-following; trading strategies; East Asian stock indices.

1. Introduction

A central challenge in quantitative finance is aligning trading strategies with prevailing market dynamics. The effectiveness of trend-following strategies, in particular, depends on the presence of persistent, directional movements in asset prices. The Hurst exponent—a robust measure of long-range dependence in time series—offers a quantitative framework for identifying such dynamics. By indicating whether a market exhibits persistent ($H > 0.5$), anti-persistent ($H < 0.5$), or random ($H \approx 0.5$) behavior, the Hurst exponent serves as a key indicator of underlying market memory.

While the application of the Hurst exponent in finance is well established—originating from hydrology and now a staple for assessing market efficiency—its use has largely been confined to theoretical

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diagnostics rather than practical implementation. Two primary methods for estimating the Hurst exponent—rescaled range (R/S) analysis and the more recent detrended fluctuation analysis (DFA)—are frequently employed, with DFA often favored for its robustness to the non-stationarities inherent in financial data. However, a significant gap persists in the literature regarding the direct use of the Hurst exponent as a real-time filter for selecting or switching trading strategies.

This study addresses this gap by systematically investigating the relationship between market persistence and the profitability of a classic trend-following approach. We analyze five prominent East Asian stock indices: SSE, N225, HSI, TAIEX, and KOSPI. Using a 10-day exponential moving average (EMA10) to generate trading signals, we compare the performance of active *long-only*, *short-only*, and *combined long-short* strategies against a passive *buy-and-hold* benchmark across different market regimes.

Our methodology involves segmenting historical data based on Hurst exponent values, calculated using both R/S and DFA, to determine which trading approach excels under specific persistence conditions. The results reveal a compelling relationship: market periods characterized by high persistence (high Hurst values) yield significantly superior returns for the active combined long-short strategy, with DFA emerging as the more reliable estimator for identifying these opportunities. Conversely, in low-Hurst environments, the passive buy-and-hold strategy consistently outperforms active trend-following.

These findings provide empirical evidence that the Hurst exponent can function as an effective regime-switching indicator. By integrating this measure of market memory into trading systems, practitioners can better tailor their strategies to the evolving structure of the market, thereby enhancing returns and managing strategy risk.

2. Literature Review

The Hurst exponent, a measure of long-range dependence, has become a cornerstone of quantitative financial analysis. Originally developed by Hurst [1] in hydrology, its application in finance stems from its ability to quantify the "memory" within a time series, providing insights into market efficiency and the predictability of price movements. A Hurst exponent greater than 0.5 suggests persistent, or trending, behavior, whereas a value below 0.5 indicates anti-persistent, or mean-reverting, dynamics.

2.1. Methods for Estimating the Hurst Exponent. Accurate estimation of the Hurst exponent is critical, which has led to the development of several methodologies, most notably rescaled range (R/S) analysis and detrended fluctuation analysis (DFA). R/S analysis, popularized in finance by Mandelbrot and Wallis [2], was among the first methods to identify long-range dependence, even in non-Gaussian series. However, its sensitivity to short-range dependencies and non-stationarities motivated the creation of more robust techniques. Peng et al. [3] introduced DFA specifically to address non-stationary trends, making it a preferred method for analyzing noisy and complex financial time series. Comparative studies, such as Kristoufek [9], have underscored the trade-offs: DFA generally provides more reliable estimates for long, non-stationary data, while R/S analysis can be advantageous for smaller datasets due to its tighter confidence intervals.

2.2. **Applications of the Hurst Exponent in Financial Markets.** A substantial body of research has employed the Hurst exponent to assess market efficiency and forecastability. Early studies used the exponent as a proxy for the Efficient Market Hypothesis, where values deviating from 0.5 imply some degree of market predictability. For instance, Eom et al. [4] found a strong positive correlation between Hurst exponent values and the predictability of price direction in global markets. Similarly, Cajueiro and Tabak [5] used the Hurst exponent to track the evolution of market efficiency in emerging markets, finding a general but inconsistent trend toward greater efficiency over time.

Recent studies have leveraged the Hurst exponent as a practical input for forecasting models and timing indicators. Chaiya et al. [6] demonstrated that higher Hurst values in the Thai stock market were associated with improved neural network forecasting performance. Shah et al. [8] developed a "Moving Hurst" indicator for enhanced trade timing in the Indian market, especially during high volatility periods. Martínez et al. [10] confirmed the varying nature of long-range dependence across European asset classes, emphasizing that persistence is not a monolithic property but depends on market and crisis conditions.

2.3. **Hurst Exponent and Technical Trading Strategies.** The natural progression from identifying market persistence is its integration into trading strategy design. Mitra [7] provided foundational evidence by linking DFA-estimated Hurst exponents to the performance of simple moving average strategies, confirming that persistence is a key driver of trend-following profitability. Vantuch [12] expanded on this by incorporating the Hurst exponent into more complex systems using indicators like RSI and CCI, though with variable results depending on the market.

Adding further depth, Tzouras et al. [11] distinguished between memory in returns and in volatility. They showed that a high Hurst exponent in returns is crucial for directional predictability, while persistence in volatility is mainly relevant for risk management. This distinction highlights the need for a nuanced application of the Hurst exponent in strategy design.

2.4. **Gaps in the Literature.** From the preceding review, several critical gaps are evident. While the relationship between persistence and trend-following profitability is established, few studies have systematically compared how different Hurst estimation methods (R/S vs. DFA) affect practical trading strategy performance. Furthermore, much of the literature either focuses on a single market or considers broad global indices, with few comparative analyses across the major East Asian markets. Finally, prior work has often stopped at demonstrating correlation, rather than operationalizing the Hurst exponent as a dynamic regime-switching filter between active and passive approaches.

This study addresses these shortcomings by: (1) rigorously comparing the performance of a trend-following strategy conditioned on Hurst values derived from both R/S and DFA; (2) applying this framework across five major East Asian stock indices; and (3) explicitly evaluating the Hurst exponent as a tool for determining when to engage in active trend-following versus adopting a passive buy-and-hold approach.

3. Methodology

3.1. **Data Description.** This study utilizes daily closing price data for five major East Asian stock indices: SSE, N225, HSI, TAIEX, and KOSPI, as detailed in Table 1. Data were collected from the TradingView platform and encompass 2,560 trading days for each index, ending on May 31, 2025. For the analysis, daily logarithmic returns were computed as $r_t = \log(P_t/P_{t-1})$, where P_t is the closing price on day t.

Table 1. Selected stock indices and their corresponding regions.

Index	Full Name	Country/Region
SSE	Shanghai Stock Exchange Composite Index	China
N225	Nikkei 225	Japan
HSI	Hang Seng Index	Hong Kong
TAIEX	Taiwan Capitalization Weighted Stock Index	Taiwan
KOSPI	Korea Composite Stock Price Index	South Korea

3.2. **Measuring the Hurst Exponent.** The Hurst exponent (H) quantifies the degree of long-range dependence in a time series. To ensure robust analysis, we estimated H using two widely used techniques: the classical rescaled range (R/S) analysis and the more recent detrended fluctuation analysis (DFA). To analyze temporal variations in persistence, each 2,560-day index series was divided into 40 non-overlapping segments of 64 trading days (approximately one trading quarter). This segment length provides a good balance between having a sufficient sample size for stable estimation and being sensitive to regime shifts. For every 64-day segment, the Hurst exponent was estimated using both R/S and DFA, as described below.

3.3. **Rescaled Range (R/S) Analysis.** Rescaled range analysis, originally developed by H.E. Hurst, is a classic method for detecting long-term memory in time series. The steps for estimating the Hurst exponent using this approach are as follows:

Let $X_1, X_2, \ldots, X_{2^N}$ (with $N \geq 5$) be a time series of length 2^N. For each block size $n \in \{2^4, 2^5, \ldots, 2^N\}$ and block index $k \in \{0, 1, \ldots, \frac{2^N}{n} - 1\}$, proceed as follows:

(1) Compute the mean of the k-th block:

$$m_{n,k} = \frac{1}{n} \sum_{i=1}^{n} X_{kn+i}.$$

(2) Center the data:

$$Y_{n,k,t} = X_{kn+t} - m_{n,k}, \quad \text{for } t = 1, \ldots, n.$$

(3) Calculate cumulative deviations:

$$Z_{n,k,t} = \sum_{i=1}^{t} Y_{n,k,i}.$$

(4) Compute the range of cumulative deviations:

$$R(n,k) = \max_{1 \le t \le n} Z_{n,k,t} - \min_{1 \le t \le n} Z_{n,k,t}.$$

(5) Compute the standard deviation:

$$S(n,k) = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} Y_{n,k,i}^2}.$$

The average rescaled range is then:

$$\frac{R}{S}(n) = \frac{n}{2^N} \sum_{k=0}^{\frac{2^N}{n}-1} \frac{R(n,k)}{S(n,k)}.$$

The Hurst exponent is estimated as the slope of the ordinary least squares regression line on the log-log plot:

$$\log\left(\frac{R}{S}(n)\right) = \log(c) + H \log(n).$$

3.4. **Detrended Fluctuation Analysis (DFA).** Detrended fluctuation analysis (DFA), introduced by Peng et al., is designed to overcome the sensitivity of R/S analysis to non-stationarities that are common in financial data. DFA measures persistence after removing local trends from the time series.

Let $X_1, X_2, \ldots, X_{2^N}$ be the input time series. The DFA procedure involves the following steps:

(1) Compute the mean:

$$\bar{X} = \frac{1}{2^N} \sum_{i=1}^{2^N} X_i.$$

(2) Construct the cumulative sum (profile):

$$Y_t = \sum_{i=1}^{t} (X_i - \bar{X}), \quad t = 1, \ldots, 2^N.$$

(3) For each window size n, divide Y_t into $\frac{2^N}{n}$ non-overlapping segments and fit a linear trend $Y_{n,k}^{\text{fit}}(t)$ to each segment.

(4) Calculate the detrended fluctuation for each segment:

$$F(n,k) = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Y_{kn+t} - Y_{n,k}^{\text{fit}}(t)\right)^2}.$$

(5) Compute the average fluctuation:

$$F(n) = \sqrt{\frac{n}{2^N}\sum_{k=0}^{\frac{2^N}{n}-1} F(n,k)^2}.$$

Like R/S analysis, the Hurst exponent is estimated as the slope of the log-log plot:

$$\log(F(n)) = \log(c) + H\log(n).$$

The DFA method's robustness to nonstationary trends makes it especially suitable for analyzing financial markets.

3.5. **Threshold Calibration via Monte Carlo Simulation.** To establish objective thresholds for classifying the Hurst exponent as low, medium, or high—and to validate our estimators—we performed a Monte Carlo simulation. This procedure enables observation of R/S and DFA estimator behavior under the null hypothesis of a random process.

We generated 10,000 synthetic Gaussian random walk time series, each of length 64 (matching our rolling window size), which have a theoretical Hurst exponent of $H = 0.5$. For each series, we computed the Hurst exponent via both R/S and DFA. The entire simulation was repeated 10 times to ensure result stability. The mean and standard deviation of each estimator are summarized in Table 2.

TABLE 2. Estimated Hurst exponents from Monte Carlo simulation of random walks ($H = 0.5$)

Round	**R/S Analysis**		**DFA**	
	Sim. H	**Std.**	**Sim.** H	**Std.**
1	0.6002	0.0820	0.5003	0.1545
2	0.6016	0.0824	0.5031	0.1548
3	0.6002	0.0829	0.5025	0.1555
4	0.5989	0.0814	0.5009	0.1570
5	0.6003	0.0827	0.5042	0.1552
6	0.6001	0.0824	0.4999	0.1549
7	0.5987	0.0814	0.5005	0.1559
8	0.6005	0.0820	0.5015	0.1553
9	0.6010	0.0822	0.5004	0.1564
10	0.6001	0.0825	0.4989	0.1543
Mean	**0.6002**	**0.0822**	**0.5012**	**0.1554**
Std. of Mean	0.0009		0.0016	

The simulation reveals clear characteristics of each estimator: R/S analysis displays a notable upward bias, consistently producing an average estimate $H \approx 0.60$ for a truly random process (a known limitation). In contrast, DFA provides estimates centered near $H = 0.50$, though with higher variance.

These empirical distributions are crucial for our classification scheme, allowing us to define robust, estimator-specific thresholds. For instance, to identify a persistent regime via R/S, H must be substantially greater than the (biased) mean of 0.60, while for DFA thresholds are set relative to 0.50. This data-driven approach ensures that regime classification is matched to the actual behavior of each method.

Based on the simulation, thresholds were defined using the mean (μ) and standard deviation (σ) for each estimator:

- **Low Hurst (Anti-persistent):** $H < \mu - 0.5\sigma$
- **Medium Hurst (Random-like):** $\mu - 0.5\sigma \leq H \leq \mu + 0.5\sigma$
- **High Hurst (Persistent):** $H > \mu + 0.5\sigma$

This resulted in the numerical thresholds shown in Table 3.

TABLE 3. Empirically Derived Thresholds for Hurst Exponent Regimes.

Estimator	**Low** (H)	**Medium** (H)	**High** (H)
R/S Analysis	< 0.56	$[0.56, 0.64]$	> 0.64
DFA	< 0.42	$[0.42, 0.58]$	> 0.58

3.6. **Trading Strategy Design and Evaluation.** Trading signals were generated using a 10-day Exponential Moving Average (EMA10). Signals were defined as:

- **Buy signal:** Closing price crossing above the EMA10
- **Sell signal:** Closing price crossing below the EMA10

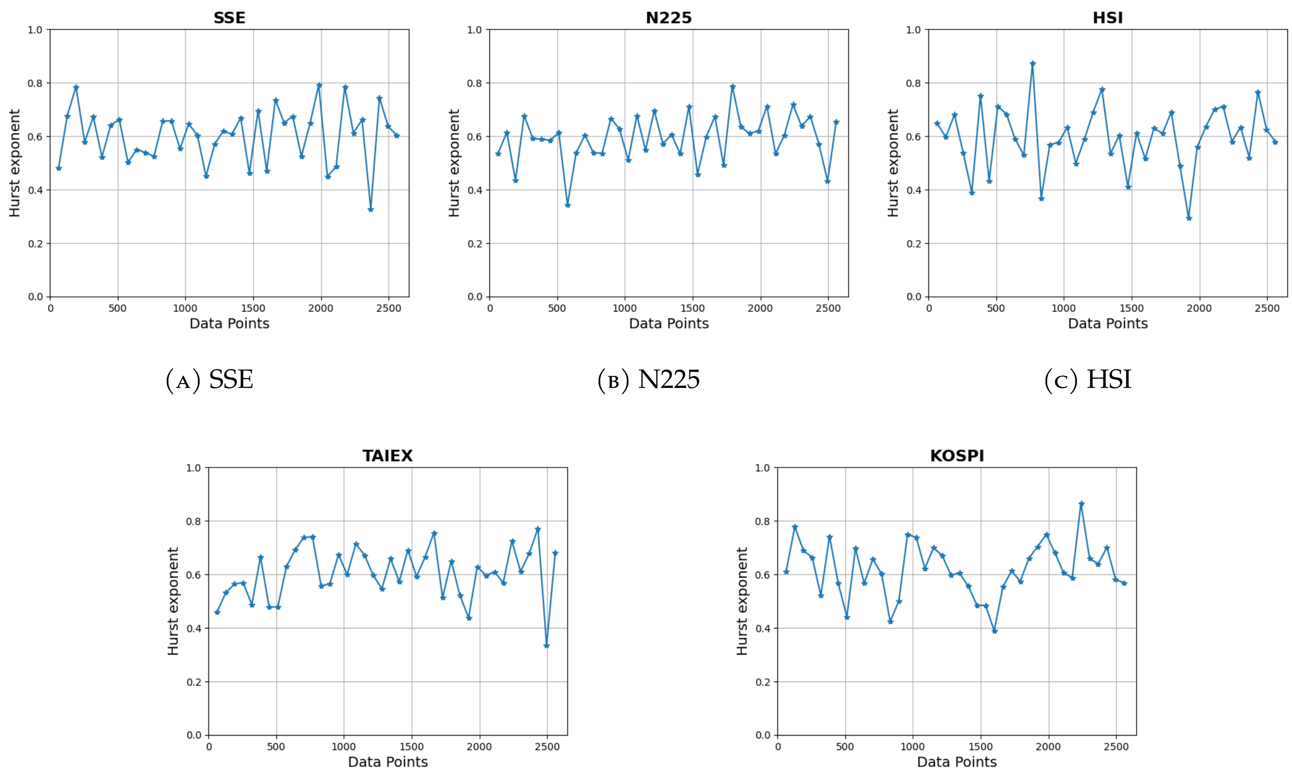
We implemented and evaluated four strategies:

(1) **Buy-and-hold:** Index purchased at the opening price on day one and sold at closing on the last day.
(2) **Long-only:** Long positions initiated on buy signals, closed on sell; no short positions taken.
(3) **Short-only:** Short positions initiated on sell signals, closed on buy; no long positions taken.
(4) **Combined long-short:** The portfolio is always in the market, switching between long and short according to trading signals.

Each strategy was evaluated within every 64-day segment. Performance within each segment was measured by total percentage return, and results were aggregated according to the segment's pre-determined Hurst regime.

4. Results

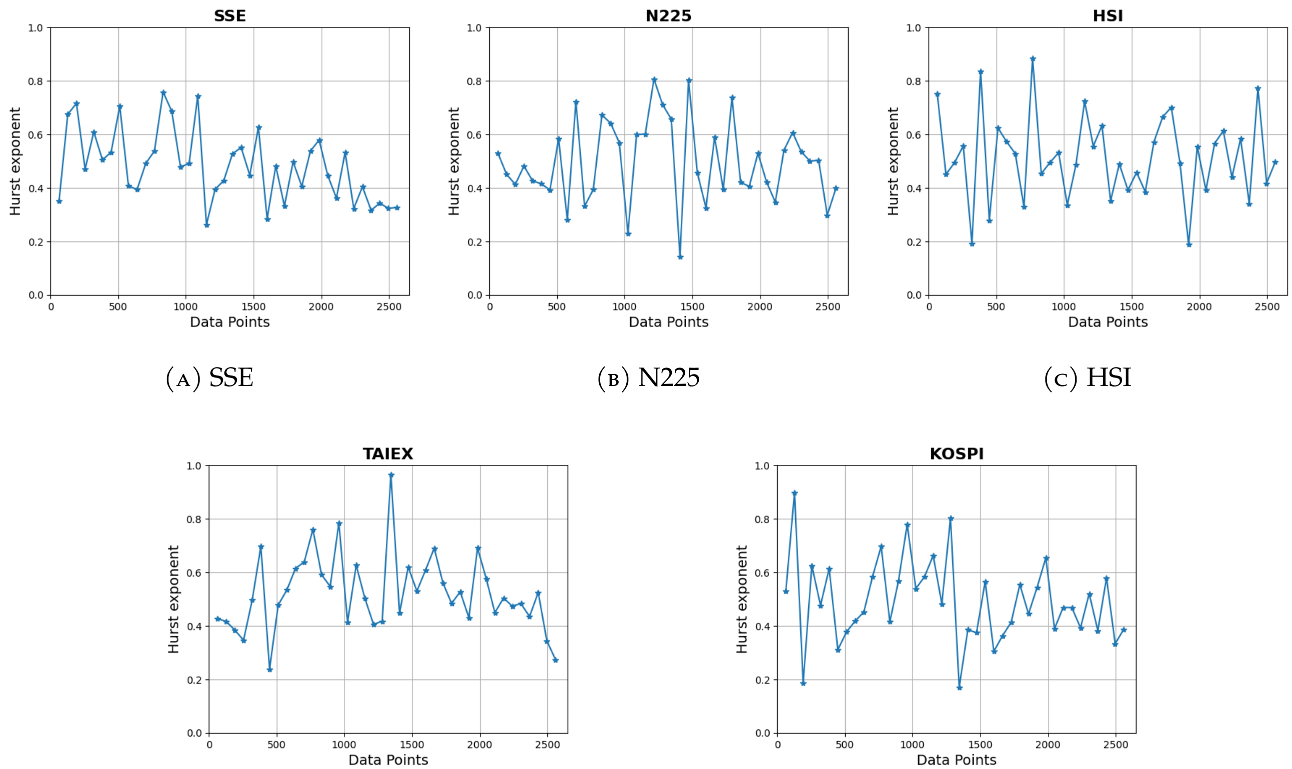
4.1. **Time-Varying Market Persistence.** Our first step was to confirm that market persistence is not static. By estimating the Hurst exponent over rolling 64-day segments, we observe significant fluctuations over time across all five indices. This dynamic behavior is visualized in Figures 1 and 2, which plot the time series of Hurst exponents calculated using R/S analysis and DFA, respectively.



(A) SSE (B) N225 (C) HSI

(D) TAIEX (E) KOSPI

Figure 1. Time-varying Hurst exponents estimated via R/S analysis. Each point represents the H value for a 64-day segment over the 2,560-day period.



(A) SSE (B) N225 (C) HSI

(D) TAIEX (E) KOSPI

FIGURE 2. Time-varying Hurst exponents estimated via DFA. Each point represents the H value for a 64-day segment. The variation illustrates shifts between persistent, anti-persistent, and random-walk behavior.

The distribution of these segments across the three persistence regimes is summarized in Table 4, confirming that each market spends a considerable amount of time in each state, which validates the premise of a regime-switching approach.

TABLE 4. Distribution of 40 Total 64-day Segments Across Hurst Regimes

Index	**R/S Analysis**			**DFA**		
	Low	Medium	High	Low	Medium	High
SSE	14	8	18	15	17	8
N225	13	16	11	14	13	13
HSI	15	11	14	11	18	11
TAIEX	11	13	16	9	19	12
KOSPI	9	14	17	16	14	10

4.2. **Strategy Performance Across Persistence Regimes.** To test the efficacy of the Hurst exponent as a regime filter, we evaluated four distinct trading strategies within the three persistence regimes. A summary of the best-performing strategy for each regime is presented in Tables 5 and 6, followed by the comprehensive results in Table 7.

TABLE 5. Best-Performing Strategy by Hurst Exponent Regime (R/S Analysis)

	Best Strategy (Average Return %)		
Index	**Low**	**Medium**	**High**
SSE	Buy-and-Hold (2.60)	Buy-and-Hold (3.93)	**Combined L-S (5.34)**
N225	Buy-and-Hold (2.19)	Buy-and-Hold (2.42)	Buy-and-Hold (1.48)
HSI	Buy-and-Hold (2.83)	Short-Only (1.06)	Short-Only (-0.06)
TAIEX	Buy-and-Hold (-0.31)	Buy-and-Hold (6.13)	**Combined L-S (4.39)**
KOSPI	Buy-and-Hold (4.44)	Combined L-S (3.44)	**Combined L-S (3.67)**
Avg.	**Buy-and-Hold (2.32)**	**Buy-and-Hold (2.23)**	**Combined L-S (2.69)**

TABLE 6. Best-Performing Strategy by Hurst Exponent Regime (DFA)

	Best Strategy (Average Return %)		
Index	**Low**	**Medium**	**High**
SSE	Buy-and-Hold (3.41)	Buy-and-Hold (2.16)	**Combined L-S (11.60)**
N225	Buy-and-Hold (1.00)	Buy-and-Hold (1.13)	Buy-and-Hold (4.23)
HSI	Buy-and-Hold (2.48)	Buy-and-Hold (-1.04)	**Combined L-S (3.46)**
TAIEX	Buy-and-Hold (0.13)	Buy-and-Hold (4.11)	**Combined L-S (4.03)**
KOSPI	Buy-and-Hold (4.77)	Combined L-S (1.82)	**Combined L-S (3.43)**
Avg.	**Buy-and-Hold (2.61)**	**Buy-and-Hold (1.31)**	**Combined L-S (4.35)**

TABLE 7. Average 64-Day Returns (%) Across Strategies and Hurst Regimes

Index	Strategy	R/S Analysis Low ($H < 0.56$)	R/S Analysis Medium ($0.56 \leq H \leq 0.64$)	R/S Analysis High ($H > 0.64$)	DFA Low ($H < 0.42$)	DFA Medium ($0.42 \leq H \leq 0.58$)	DFA High ($H > 0.58$)
SSE	Buy-and-Hold	2.60	**3.93**	0.19	**3.41**	2.16	−2.05
	Long-Only	−0.95	1.53	0.60	1.69	−1.86	2.01
	Short-Only	−2.02	−1.45	1.14	−1.42	−1.56	3.56
	Combined L-S	−1.35	1.97	5.34	1.74	−1.53	**11.60**
N225	Buy-and-Hold	2.19	**2.42**	1.48	1.00	1.13	**4.23**
	Long-Only	−1.28	−0.28	0.50	−2.72	−0.20	1.93
	Short-Only	−2.77	−2.31	−0.11	−2.30	−0.59	−2.64
	Combined L-S	−2.03	−1.59	0.97	−3.95	−0.58	1.67
HSI	Buy-and-Hold	**2.83**	−0.31	−1.14	**2.48**	−1.04	1.32
	Long-Only	−2.86	−2.76	−2.28	−2.63	−3.78	−0.74
	Short-Only	−5.24	1.06	−0.06	−2.83	−1.88	−0.26
	Combined L-S	0.10	−0.68	−2.51	−3.06	−2.53	**3.46**
TAIEX	Buy-and-Hold	−0.31	**6.13**	1.56	0.13	**4.11**	1.83
	Long-Only	−2.60	3.32	1.97	−1.30	2.17	1.38
	Short-Only	−2.52	−1.57	−0.29	−3.00	−1.37	0.02
	Combined L-S	−2.05	3.96	4.39	−1.93	3.60	**4.03**
KOSPI	Buy-and-Hold	**4.44**	−0.59	0.78	**4.77**	−0.32	−2.67
	Long-Only	−0.49	0.36	−0.32	1.29	−0.60	−1.70
	Short-Only	−2.06	0.75	1.58	−0.81	0.87	1.97
	Combined L-S	0.17	3.44	3.67	3.27	1.82	**3.43**
Average	Buy-and-Hold	**2.32**	**2.23**	0.55	**2.61**	**1.31**	0.89
	Long-Only	−1.71	0.41	0.14	−0.51	−0.86	0.60
	Short-Only	−3.05	−0.73	0.40	−1.92	−1.01	0.21
	Combined L-S	−1.05	1.33	**2.69**	−0.43	0.18	**4.35**

Note: The "Average" row in Table 7 represents a weighted average, where the returns for each index are weighted by the number of segments it contributed to that specific regime (as detailed in Table 4).

The empirical results in Tables 5, 6, and 7 reveal a powerful, consistent pattern: the optimal trading strategy is strongly conditional on the market's memory, as measured by the Hurst exponent. This regime-conditional approach provides a more representative measure of aggregate performance than a static, non-conditional strategy.

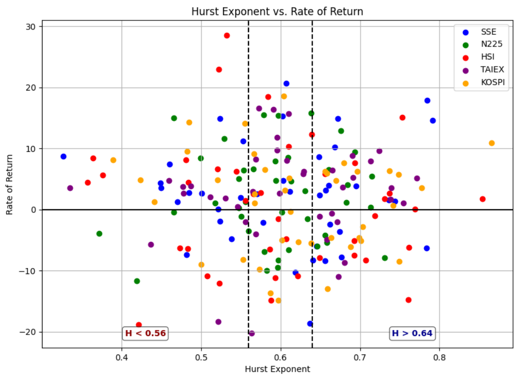
The most compelling evidence is found with the ***combined long-short*** strategy. This trend-following approach thrives in high-persistence environments. Under the DFA filter, it yields a weighted average return of **4.35%** in the high-Hurst regime, making it not only the best strategy for that regime but the best performer across all combinations. This outperformance is driven by exceptional returns in specific trending periods, such as for the SSE (11.60%). This confirms the core hypothesis that trend-following is most profitable in persistent markets.

Conversely, a passive ***buy-and-hold*** strategy is most effective in exactly the opposite condition: the low-persistence, or anti-persistent, regime. With a weighted average return of **2.61%** (DFA) in these markets, this simple approach is more robust than active strategies, which suffer from "whipsaw" trades and incur losses in mean-reverting environments. Indeed, the combined long-short strategy produced a negative average return of **-0.43%** under these same conditions.

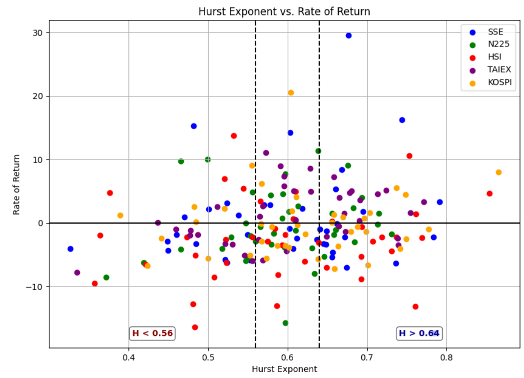
The performance of the standalone ***long-only*** and ***short-only*** strategies provides additional context. While both show a slight preference for high-persistence regimes, their average returns are modest and inconsistent, highlighting the importance of capturing both upward and downward trends, which the combined strategy does effectively.

Finally, a crucial finding is the superior efficacy of DFA as an estimator. For the combined long-short strategy in high-persistence regimes, DFA identified periods leading to a **4.35%** average return, substantially higher than the **2.69%** identified using R/S. This suggests DFA is a more reliable filter for practical implementation.

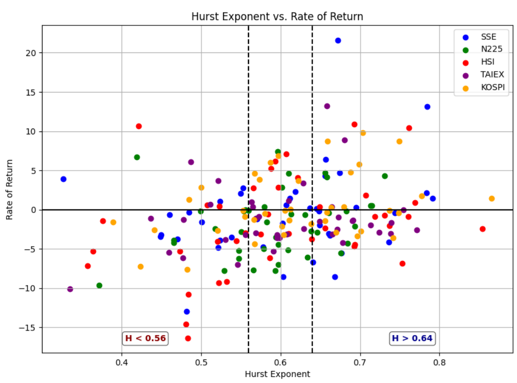
4.3. **Visualizing the Hurst-Return Relationship.** To further investigate this relationship, Figures 3 and 4 plot the Hurst exponent against the 64-day returns for each strategy. These visualizations complement the aggregated results by showing the distribution and variance of outcomes.



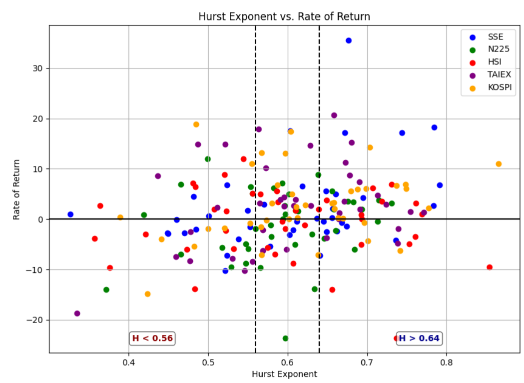
(A) Buy-and-Hold



(B) Long-Only



(C) Short-Only



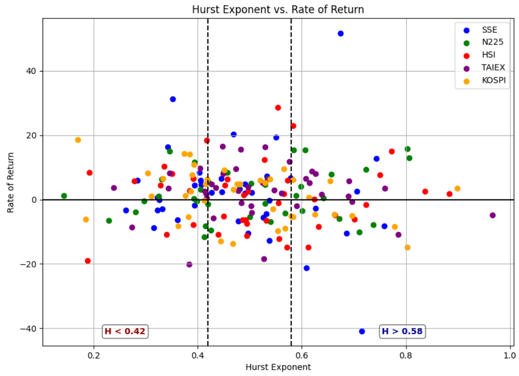
(D) Combined Long-Short

FIGURE 3. Scatter plots of strategy returns versus the Hurst exponent estimated via R/S analysis across all indices.

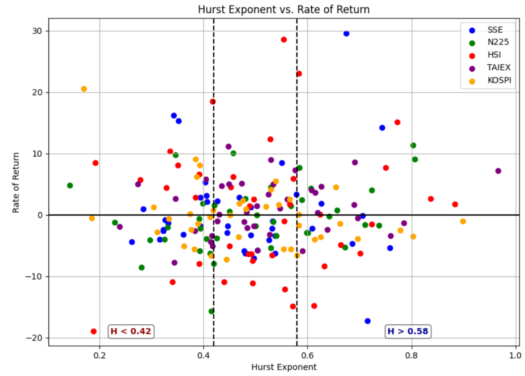
The visualizations powerfully illustrate the regime-dependent nature of the strategies. While most plots show a noisy relationship, the scatter plot for the ***combined long-short*** strategy under the **DFA estimator** (Figure 4d) reveals a clear structure. In the low-Hurst regime ($H < 0.42$), returns are dispersed with a negative skew, confirming that trend-following is ineffective in anti-persistent markets. As the Hurst exponent increases, the return distribution shifts upwards. Most strikingly, the high-Hurst regime ($H > 0.58$) contains the vast majority of the strategy's large positive outcomes, with numerous periods generating returns above 20%.

However, the plots also highlight a crucial risk-reward tradeoff: the high-persistence regime that unlocks the greatest profits also exhibits significant return volatility. This is characteristic of trend-following, where large gains are often punctuated by sharp drawdowns.

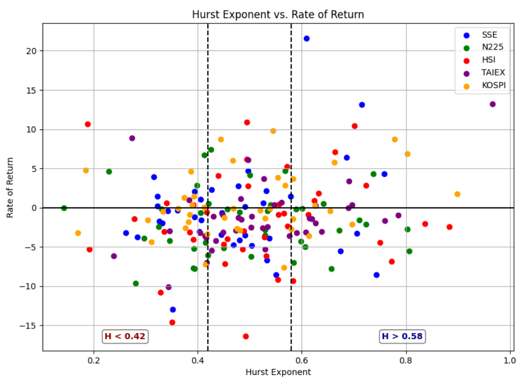
Ultimately, these figures provide compelling visual evidence that the Hurst exponent, particularly when estimated with DFA, serves as an effective filter for market conditions. By aligning strategy



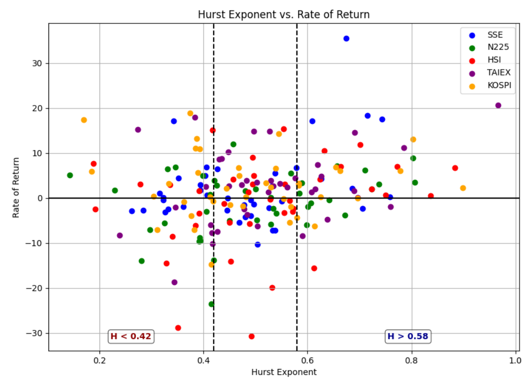
(A) Buy-and-Hold



(B) Long-Only



(C) Short-Only



(D) Combined Long-Short

FIGURE 4. Scatter plots of strategy returns versus the Hurst exponent estimated via DFA across all indices.

selection with market memory, traders can systematically position themselves to capitalize on persistent trends while avoiding the unprofitable whipsaws of anti-persistent environments.

5. Discussion

Our empirical results provide compelling evidence that the Hurst exponent is an effective indicator for market regime classification, enabling the dynamic selection of trading strategies. The findings align with the theoretical underpinnings of market dynamics and offer practical insights for systematic traders. This discussion interprets these findings and considers their practical implications.

5.1. **Interpretation of Key Findings.** The clear divergence in optimal strategy performance across Hurst-defined regimes corroborates the central hypothesis of this study. The relationship between market memory and strategy success can be interpreted as follows:

(1) **High-Persistence Regimes (DFA: $H > 0.58$):** These periods are characterized by significant positive autocorrelation, meaning past price movements are likely to continue. This is the ideal environment for trend-following systems, as they are designed to capitalize on sustained directional moves. The ***combined long-short*** strategy excels here because it agnostically profits from both strong uptrends and pronounced downtrends, which are hallmarks of a persistent market. The exceptional average return of **4.35%** (using the DFA filter) underscores the profitability of applying trend-following precisely when market conditions are favorable.

(2) **Low-Persistence Regimes (DFA: $H < 0.42$):** In these anti-persistent, or mean-reverting, markets, price movements are more likely to reverse. Any trend signal, such as a moving average crossover, is likely to be a "whipsaw"—a false signal that quickly reverses, leading to losses. Active strategies based on such signals are therefore systematically penalized. Our results confirm this, showing that trend-following strategies underperform. In this environment, the most rational approach is to avoid active trading, making a passive ***buy-and-hold*** strategy superior by default, as it avoids the losses associated with false signals.

(3) **The Superiority of DFA:** A key contribution of this study is the direct comparison of R/S analysis and DFA as signal generators. Our findings consistently show that **DFA provides a cleaner and more profitable filter**. The average return for the combined strategy in high-Hurst regimes identified by DFA was 4.35%, substantially outperforming the 2.69% for regimes identified by R/S. This empirical result has a strong theoretical basis: financial time series are known to contain non-stationarities and underlying trends. DFA provides a more reliable estimate because it is designed to ignore long-term market trends, which can easily distort the R/S method. This robustness likely allows DFA to more accurately isolate the true long-range memory of the market, leading to a more reliable signal for strategy switching.

5.2. **Practical Implications.** The findings suggest that the Hurst exponent can be used as a practical "meta-strategy" or a dynamic overlay for portfolio management. Rather than being a trading signal itself, it acts as a filter that dictates which type of strategy to deploy. A systematic framework could be implemented as follows:

- Calculate the rolling Hurst exponent of a market using DFA over a lookback window (e.g., 64 days).
- If the exponent rises above a predefined threshold (e.g., $H > 0.58$), activate a trend-following system (like the EMA10 crossover strategy).
- If the exponent falls below a lower threshold (e.g., $H < 0.42$), deactivate the trend-following system and revert to a passive holding or potentially deploy a mean-reversion strategy.

- In the intermediate "random walk" regime, a more cautious or passive approach would be warranted, as no strong edge is apparent.

This adaptive approach allows traders to systematically engage with markets when their strategy is most likely to be profitable and to stand aside when conditions are unfavorable, potentially enhancing long-term risk-adjusted returns.

5.3. **Limitations and Future Directions.** While the results are promising, this study has limitations that present avenues for future research. The analysis did not incorporate transaction costs or slippage, which would impact net profitability in a live environment. Furthermore, the study utilized a fixed lookback window (64 days) and specific Hurst thresholds; future work could explore dynamic optimization of these parameters. Finally, testing this Hurst-based filter on a broader range of trend-following and mean-reversion strategies could further validate its utility as a universal market timing overlay.

6. Conclusion

This study provides empirical evidence that market memory, as measured by the Hurst exponent, is a key determinant of trend-following strategy performance. We establish a clear framework: passive *buy-and-hold* strategies tend to dominate in low-persistence (mean-reverting) regimes, whereas an active *combined long-short* strategy performs particularly well during periods of high persistence (trending behavior).

Among the estimation methods, detrended fluctuation analysis (DFA) emerges as the more reliable tool compared to R/S analysis for detecting profitable trading regimes. In high-persistence periods identified by DFA, the combined strategy delivered an average 64-day return of 4.35% (17.13% annualized). These results suggest that the Hurst exponent can be elevated from a descriptive measure of long-range dependence to a practical instrument for designing adaptive trading systems. By dynamically aligning strategies with prevailing market states, practitioners may improve both returns and risk management.

Future research could extend this work by incorporating transaction costs, examining parameter sensitivity across different lookback windows, and applying the framework to a broader range of asset classes. Such investigations would further validate the robustness and practical applicability of the Hurst exponent in real-world trading environments.

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