TIME-VARYING LONG MEMORY HURST PARAMETER EVALUATIONS OF THE WTI CRUDE OIL MARKET

*Yuan Yeping, Chin Zi Yi, Chin Wen Cheong, and Lim Min**

1. Introduction

Crude oil is a fundamental commodity, closely tied to national strategies, global politics, and economic power (Guo et al., 2022). With daily consumption averaging roughly 75 million barrels, it remains one of the most critical resources in the world economy. As a result, understanding the dynamics of crude oil price movements is essential for policymakers, investors, and firms in managing risk and formulating economic strategies (Chatziantoniou et al., 2021). Sharp price increases and heightened volatility have been shown to undermine real economic growth (Urich, 2009). Consequently, the relationship between oil prices and their determinants has been widely investigated, with particular attention to long memory in returns and volatilities across commodity markets (Wang and Wu, 2012).

*Yuan Yeping and Chin Zi Yi earned their B.Sc. degrees in Mathematics and Applied Mathematics from Xiamen University Malaysia. Their research interests include financial mathematics and financial time series analysis.

Chin Wen Cheong is an Associate Professor in the Department of Mathematics at Xiamen University Malaysia. He holds a Ph.D. in Statistics from the National University of Malaysia. His research focuses on time series analysis and risk management.

Lim Min earned a B.Sc. degree in Mathematical Sciences and Applied Statistics, as well as both a master's and a Ph.D. degree in Statistics from the University of Toronto. Dr. Lim is currently an Assistant Professor in the Department of Mathematics at Xiamen University Malaysia. Her research areas include statistical modeling and structural equation modeling.

The Journal of Energy and Development, Vol. 50, Nos. 1-2

Crude oil price volatility reflects a complex set of drivers, including supply disruptions or surpluses, financial market conditions, geopolitical conflicts, embargoes, revolutions, macroeconomic growth, and broader political dynamics (Mensi et al., 2012). Historical episodes underscore this sensitivity: the Gulf War following Iraq's 1990 invasion of Kuwait, U.S. military operations in Iraq in 2003, the 1997 Asian financial crisis, the 2008 global financial crisis, and the COVID-19 pandemic beginning in 2019 all produced substantial disruptions in crude oil markets. Such events often induce price fluctuations that deviate from fundamental values, raising questions about informational efficiency.

The efficient market hypothesis (EMH) provides a key framework for evaluating whether crude oil prices fully reflect available information. EMH distinguishes between weak, semi-strong, and strong forms of efficiency, with weak-form efficiency implying that historical price data cannot systematically predict future returns (Yu et al., 2013). Research findings on the informational efficiency of oil markets, however, remain abundant yet inconclusive. In this literature, the Hurst exponent has emerged as a prominent tool, particularly in testing for long memory and deviations from random-walk behavior.

This paper contributes to the debate by examining whether the West Texas Intermediate (WTI) crude oil market exhibits weak-form efficiency over an extended period. We first calculate the Hurst exponent and then analyze its evolution through moving time windows of fixed length, searching for evidence of long memory in both returns and volatility.

Prior studies reveal mixed results. Fernandez (2010) argues that oil returns do not support even the weakest form of EMH. Narayan et al. (2010) find inefficiencies in both oil and gold markets, while Wang and Wu (2013) report less persistent price behavior for short-term contracts. Grech and Mazur (2004) highlight the use of the Hurst exponent for crisis detection. Other contributions show fluctuating efficiency across time (Tabak and Cajueiro, 2007; Kristoufek, 2019) or evidence of long memory in volatility but not returns (Wang and Wu, 2012). Additional approaches, such as detrended fluctuation analysis (Ramirez et al., 2002) and multifractal analysis (Wang and Liu, 2010), further underscore the complexity and evolving efficiency of oil markets.

To strengthen reliability, we employ three methods—aggregated variance, rescaled range (R/S) analysis, and periodogram-based analysis. Mandelbrot (1972) refined the R/S statistic, demonstrating its robustness for detecting long-range dependence even in non-Gaussian processes. While R/S analysis may slightly overestimate long memory when the Hurst exponent falls below 0.5, results generally remain qualitatively accurate (He and Qian, 2012). Periodogram-based methods offer additional advantages, including distributional properties that are independent of sample size and model specification (Akdi et al., 2023). Aggregated variance analysis, in particular, has been found more responsive to economic shocks relative to R/S and periodogram techniques.

The remainder of this paper is organized as follows. Section 2 outlines the methodology. Section 3 presents the empirical results. Section 4 concludes the paper.

2. Methodology

To estimate the Hurst exponent (Hurst, 1951), we employ three methods: the aggregated variance, the rescaled range (R/S) analysis, and the periodogram approach. Among these, the primary emphasis is placed on the R/S method, while the other two are utilized for comparative purposes. Formally, let x_t denote the price of WTI crude oil at time t, and r_t represent the logarithmic return, defined as

$$r_t = ln\,(x_t/x_{t-1}).$$

The rescaled range (R/S) method measures the range of partial sums of deviations of a time series from its mean, normalized by its standard deviation. Consider a sample of returns $\{r_1, r_2, \ldots, r_n\}$, with $\overline{r}_n$ denoting the sample mean, where n represents the block length of each non-overlapping subseries. The average $\overline{r}_n$ over all possible subseries is then computed as:

$$\overline{r}_n = \frac{1}{n}\sum_{i=1}^{n} r_i$$

The cumulative deviation from the mean of each block subseries is defined as:

$$Y_t = \sum_{i=1}^{k} (r_i - \overline{r}_n), \text{ for } k = 1,\ 2,\ \ldots,\ n.$$

The standard deviation and the range of the return series in each block can be expressed as:

$$S_n = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n} (r_i - \overline{r}_n)^2} \text{ and } R_n = \max(Y_t) - \min(Y_t)$$

Finally, we compute the rescaled range of each block with the length n, R_n/S_n. Since there is a scaling relationship between the average rescaled range of the sample and the sample length, we have:

$$\left(\frac{R_i}{S_i}\right) = c \times n^H$$

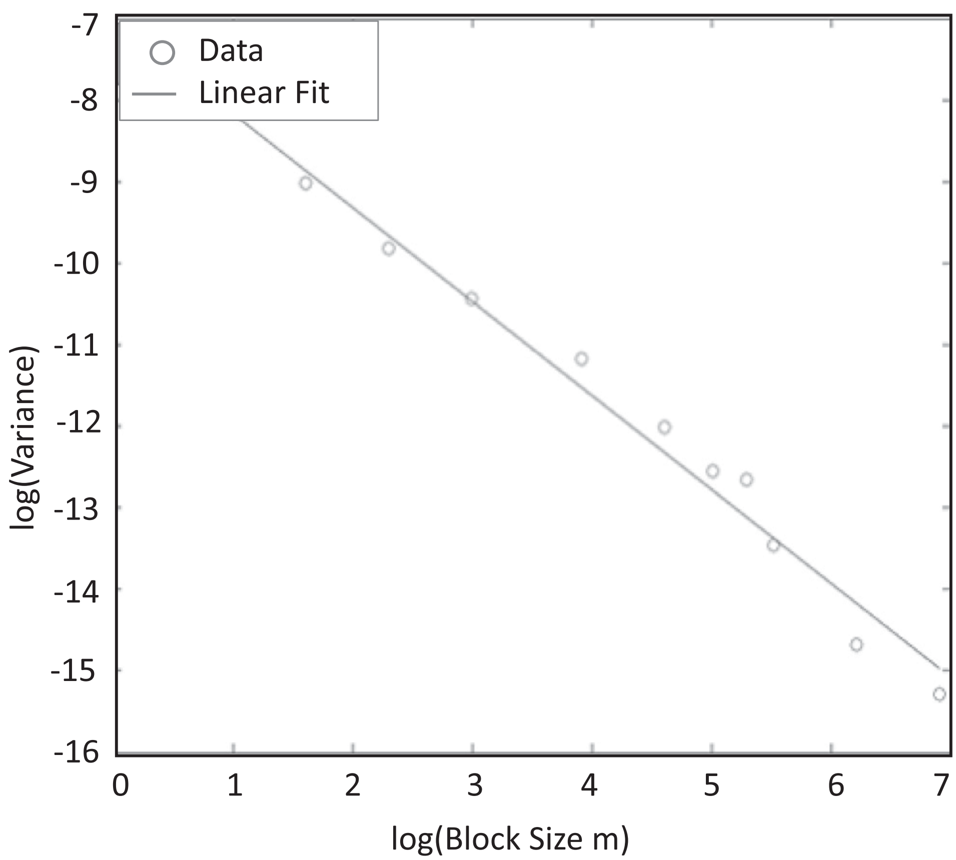
Using the R/S method, the Hurst exponent could be assessed by plotting data versus in a log–log and measuring the slope of the straight line. The Hurst exponent is given as:

$$log\left(\frac{R_i}{S_i}\right) = log\,(c) + H \cdot log\,(n)$$

where $H =$ slope. denotes the Hurst exponent. The different values of the Hurst exponent imply fundamentally different price behaviors.

- $0 \leq H < 0.5$: The series is anti-persistent. The price behavior follows a mean-reverting process.
- $H = 0.5$: The price behavior is referred to as a geometric Brownian motion.
- $0.5 < H \leq 1$: The time series is persistent with long memory.

Figure 1
AGGREGATED VARIANCE METHOD FOR RETURN, $H = 0.42358$



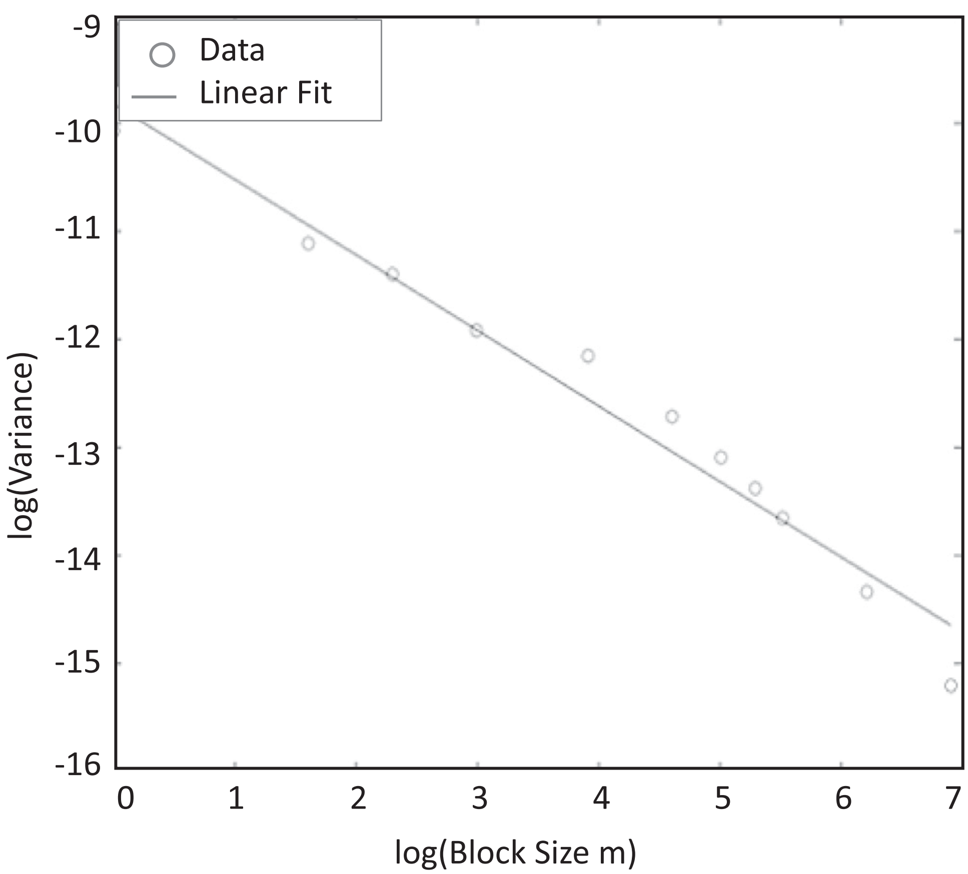
3. Empirical Study

In this study, crude oil price data were obtained from the U.S. Energy Information Administration (EIA). The dataset consists of daily closing prices for West Texas Intermediate (WTI) crude oil at Cushing, quoted in U.S. dollars per barrel. It comprises 9,821 observations covering the period from January 2, 1986, through May 13, 2024.

We examine the long-range dependence of the crude oil market using the West Texas Intermediate (WTI) index. Figures 1 and 2 present results from the aggregated variance method. The dataset was partitioned into intervals of varying lengths (1, 5, 10, 20, 50, 100, 150, 200, 250, 500, 1,000), and for each interval, returns were grouped into blocks of length n. Log-returns within each block were summed to obtain aggregated returns, from which the variance across all blocks

Figure 2

AGGREGATED VARIANCE METHOD FOR RETURN SQUARE, H = 0.65001



was calculated. These variances were then log-transformed, and a linear fit was applied to the log–log relationship between interval lengths and variances. The slope of this relationship is proportional to twice the Hurst exponent. The results show a Hurst exponent of $H = 0.42358$ for returns, indicating anti-persistent behavior and a lack of long-term dependence. By contrast, the squared returns yield $H = 0.65001$, suggesting long-term dependence in volatility and evidence of volatility clustering, where elevated volatility levels persist over extended periods.

Figures 3 and 4 display complementary results based on the rescaled range (R/S) method. Here, the return series was divided into blocks ranging from 10 observations up to half the total sample length (N), ensuring robust estimation across multiple scales. For each block size n, overlapping subsequences were constructed, and the rescaled range (R/S) was computed. The average rescaled range across all subsequences was then calculated for each block size. Plotting $\log(R/S)$

Figure 3
RESCALED RANGE ANALYSIS FOR RETURN, $H = 0.51973$

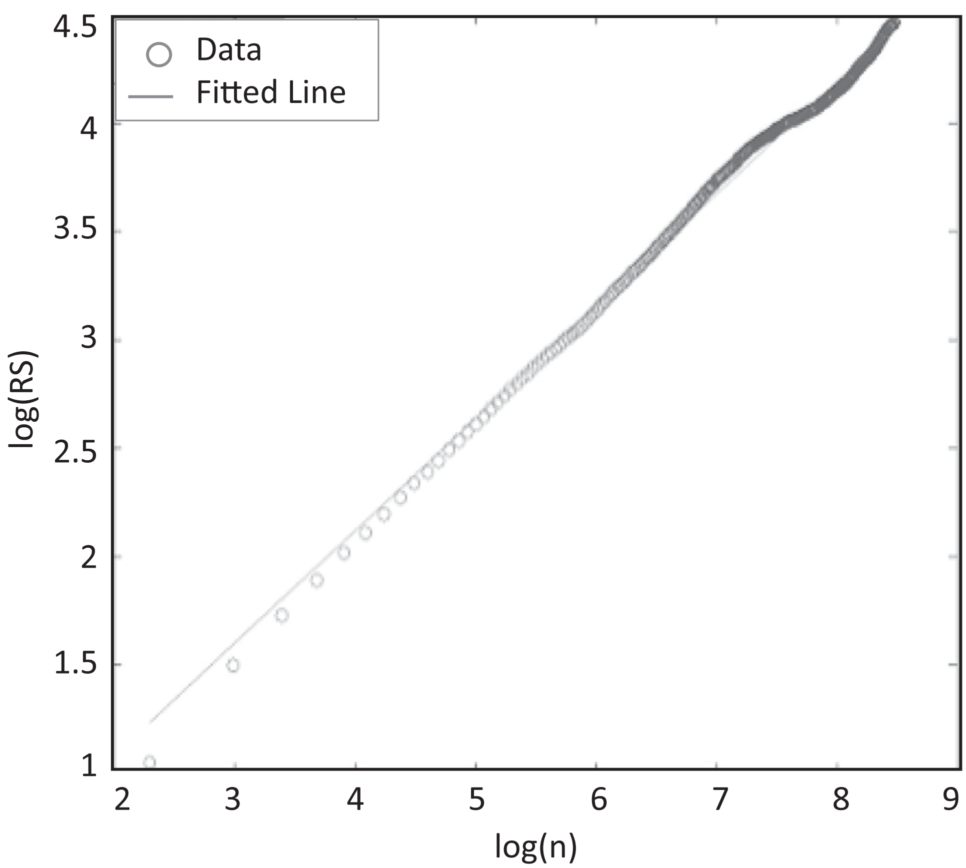
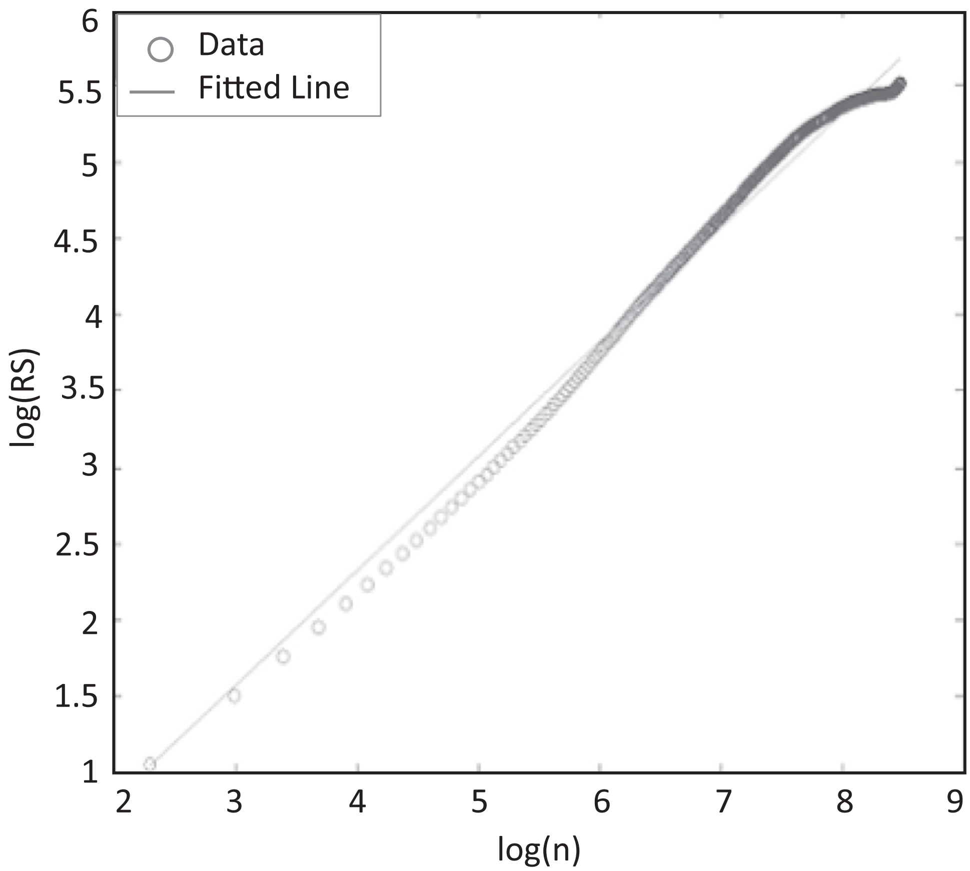


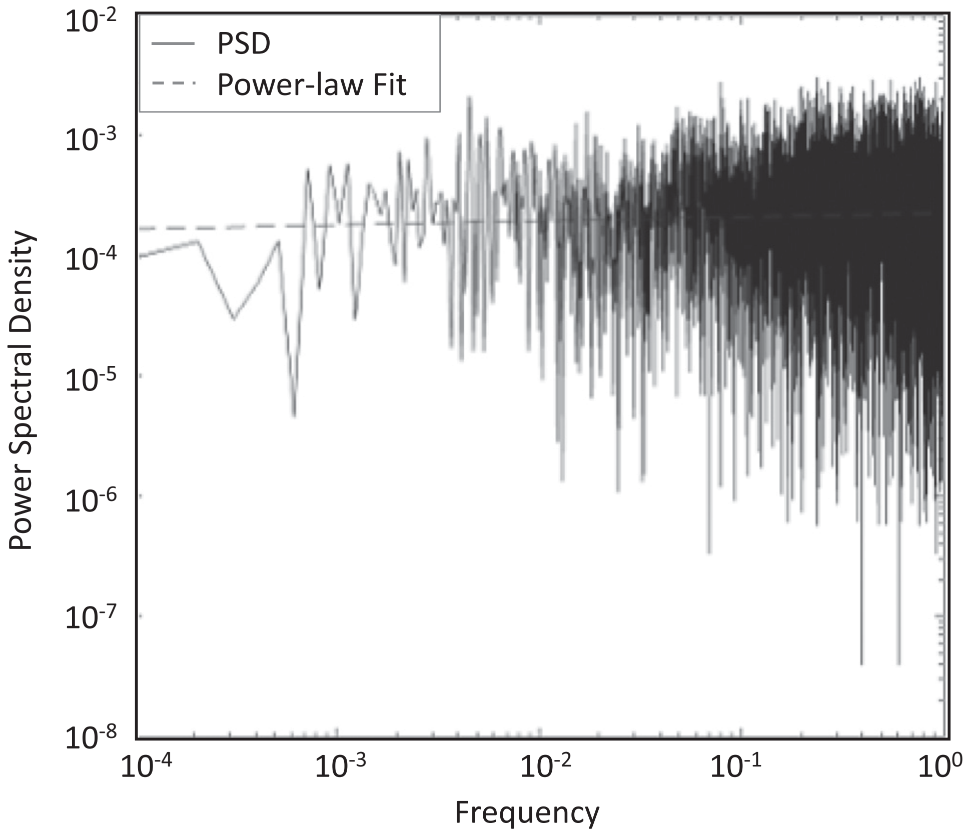
Figure 4
RESCALED RANGE ANALYSIS FOR RETURN SQUARE, $H = 0.74939$



against $\log(n)$, we estimated the slope of the fitted linear model, which corresponds to the Hurst exponent. The estimated exponent for returns is $H = 0.51973$, consistent with weak or absent long memory. However, the squared returns yield $H = 0.74939$, demonstrating persistence and long memory in volatility dynamics.

Figures 5 and 6 report the results obtained using the periodogram method. We first computed the log returns of the crude oil price series and subsequently derived the squared log returns. Applying the Fast Fourier Transform (FFT), we decomposed the squared returns into their frequency components and calculated the corresponding Power Spectral Density (PSD). Only the positive frequencies and their associated PSD values were retained for analysis. To estimate the Hurst exponent, we fitted a power law by plotting the logarithm of frequency against the logarithm of PSD values and determining the slope of the linear relationship. The estimated

Figure 5
RESCALED RANGE ANALYSIS FOR RETURN SQUARE, H = 0.74939

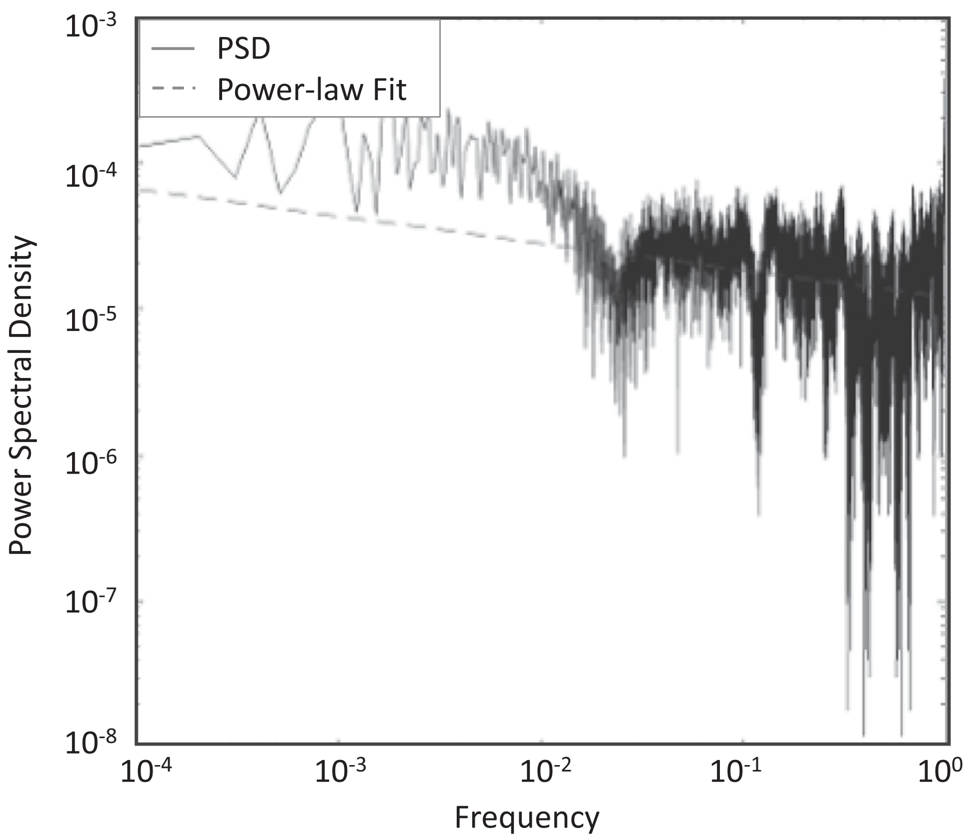


Hurst exponent for returns is $H = 0.4833$, indicating no evidence of long memory. In contrast, the squared returns yield $H = 0.59198$, suggesting persistence and long-range dependence in volatility.

The results obtained from the three methods share several common features (Table 1). Across all approaches, the estimated Hurst exponents for WTI returns are close to 0.5, suggesting that price dynamics approximate a random walk, consistent with the weak form of the efficient market hypothesis. Nevertheless, the aggregated variance and periodogram methods indicate slight anti-persistent tendencies, reflecting differences in the statistical sensitivities and time scales inherent to these techniques.

By contrast, the Hurst exponents for squared returns are substantially greater than 0.5, providing strong evidence that volatility is a persistent process. This persistence has significant implications, as it suggests that periods of heightened volatility tend to cluster and endure over time.

Figure 6
PERIODOGRAM METHOD FOR RETURN SQUARE, $H = 0.59198$

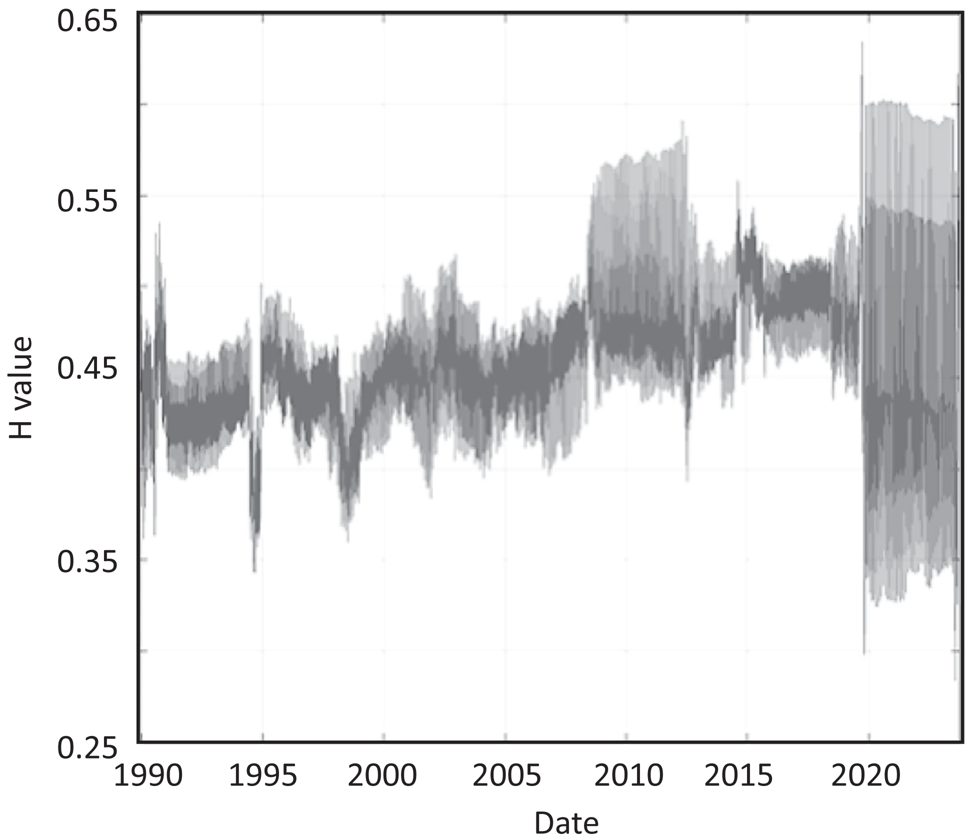


Several major global events correspond with abrupt declines in the efficiency measures: Iraq's invasion of Kuwait in 1990, the Asian financial crisis of 1997–1998, U.S. military operations in Iraq (2002–2003), the global financial crisis (2007–2009), and the COVID-19 pandemic (2019–2020). These episodes are reflected in Figures 7, 9, and 10. Figure 7, in particular, plots the time-varying Hurst exponent estimated using the aggregated variance method with a moving

Table 1
HURST EXPONENT VALUES FOR LINEAR FIT METHODS

	Aggregated Variance	**R/S Analysis**	**Periodogram Method**
Return	0.42358	0.51973	0.48330
Return Square	0.65001	0.74939	0.59198

Figure 7
TIME-VARYING *H* VALUE FOR RETURN BASED ON AGGREGATED VARIANCE ANALYSIS

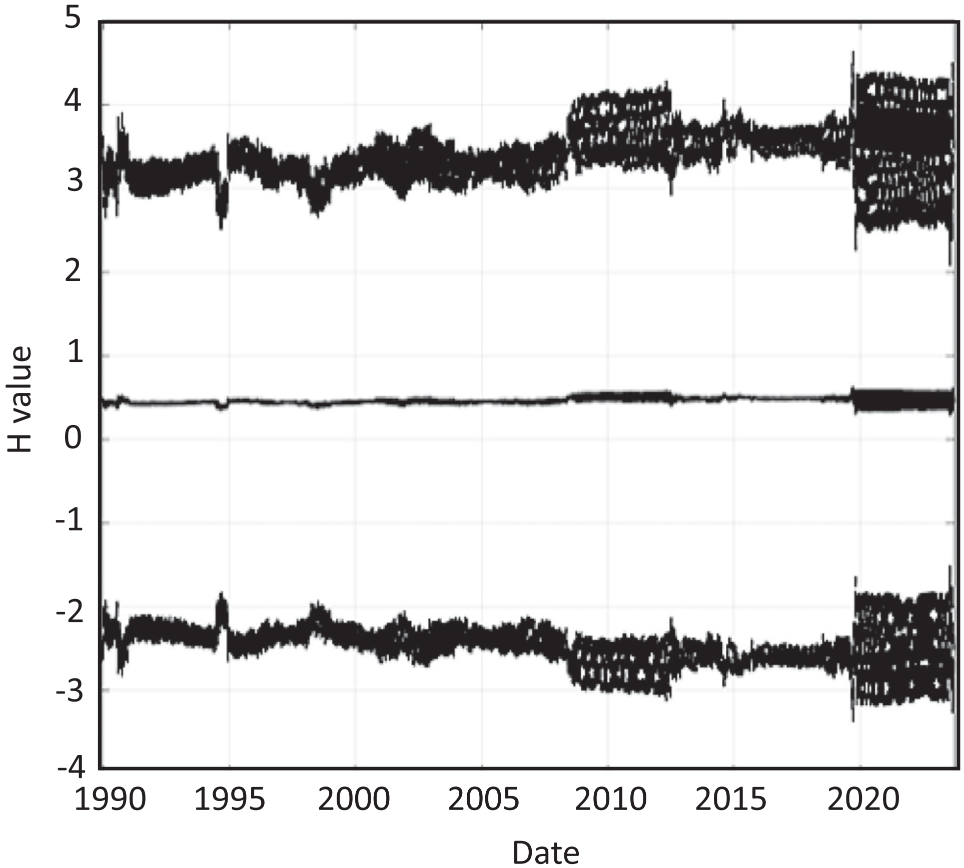


window of 1,000 observations, while Figure 8 provides the associated 95% confidence interval.

The x-axis in Figure 7 begins in 1990, corresponding to the starting point of the first estimation window (1990–1995). Subsequent values are calculated over rolling five-year periods. Between 1990 and 2009, the Hurst exponent fluctuated between 0.35 and 0.52. From 2009 to 2020, it varied within the range of 0.45 to 0.60. After 2020, the estimates became more volatile, ranging between 0.30 and 0.60. Overall, these values remain broadly consistent with the linear Hurst estimates reported earlier in Figure 1.

The time-varying Hurst exponents highlight the influence of major geopolitical and economic events on crude oil market dynamics. During Iraq's invasion of Kuwait in 1990, oil supply disruptions triggered sharp price fluctuations and a

Figure 8
TIME-VARYING *H* VALUE FOR RETURN BASED ON AGGREGATED VARIANCE WITH 95% CONFIDENCE INTERVAL



steep decline in Hurst values. In the immediate aftermath, the Hurst exponent briefly rose above 0.5, indicating weak long memory. As the conflict ended in early 1991 and supply conditions normalized, market behavior reverted toward a random walk, reflecting greater efficiency.

Between 1995 and 2005, two sharp declines in Hurst values coincided with the 1997–1998 Asian financial crisis and the U.S. military intervention in Iraq in 2003. From 2005 through 2015, the index trended upward, with values stabilizing between 0.50 and 0.55 after the global financial crisis. This suggests a modest improvement in efficiency, potentially linked to greater liquidity and the increased role of institutional investors and high-frequency traders in stabilizing the market.

Following 2019, the onset of the COVID-19 pandemic caused another sharp drop in the Hurst index. As the crisis unfolded, however, values rose above

0.5 before fluctuating around that threshold, ultimately converging toward random-walk behavior. Overall, the aggregated variance results suggest that WTI crude oil prices do not exhibit strong long memory, with Hurst exponents generally oscillating around 0.5.

Figure 9 presents the corresponding estimates using the rescaled range (R/S) method with a moving window of 1,000 observations and 95% confidence intervals. From 1990 to 1995, the Hurst exponent ranged between 0.50 and 0.65 but declined thereafter, gravitating closer to 0.5. Between 2005 and 2010, the index rose sharply from 0.40 to 0.70, before falling again post-2010 and fluctuating between 0.50 and 0.70. The overall range of values is broadly consistent with the static Hurst estimate reported earlier in Figure 3.

Between 1990 and 1995, the Hurst exponents generally remained above 0.5, indicating the presence of long memory in crude oil prices. An exception occurred

Figure 9
TIME-VARYING *H* VALUE FOR RETURN BASED ON RESCALED RANGE ANALYSIS WITH 95% CONFIDENCE INTERVAL

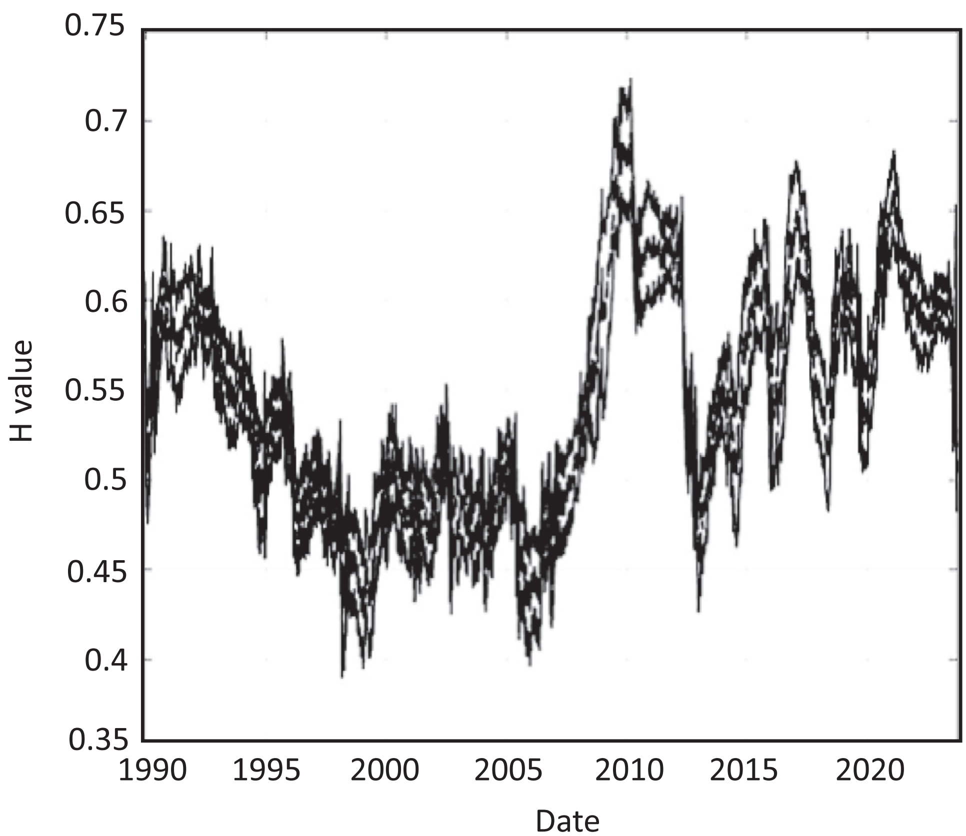
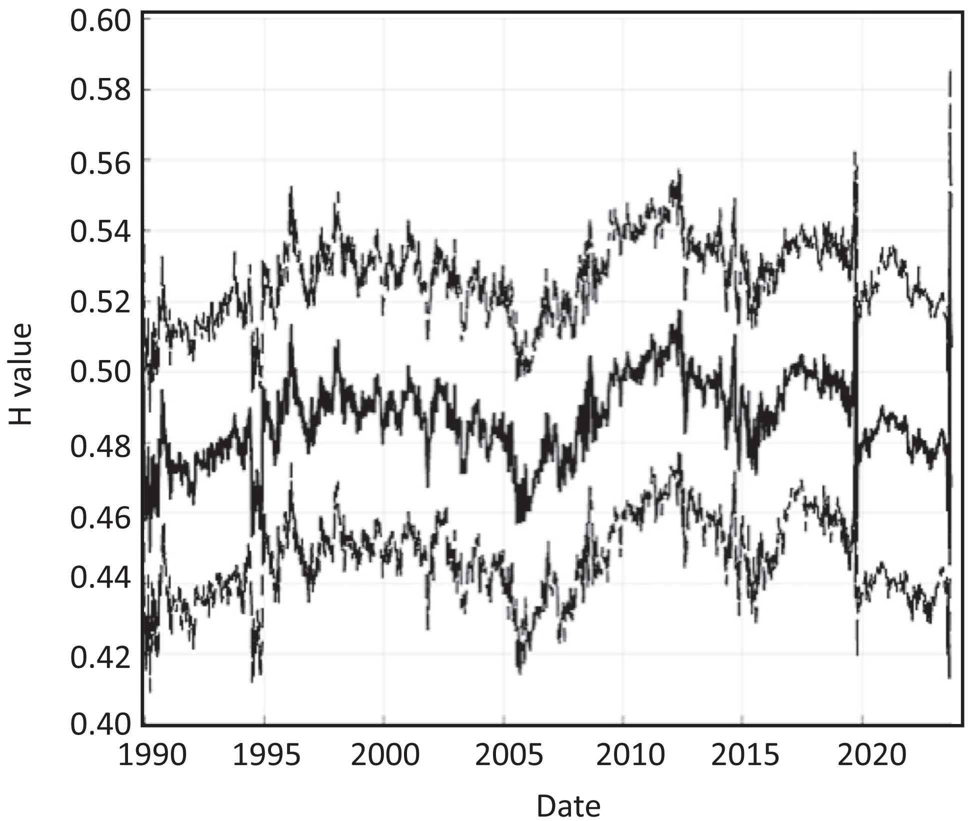


Figure 10
TIME-VARYING *H* VALUE FOR RETURN BASED ON PERIODOGRAM ANALYSIS WITH 95% CONFIDENCE INTERVAL

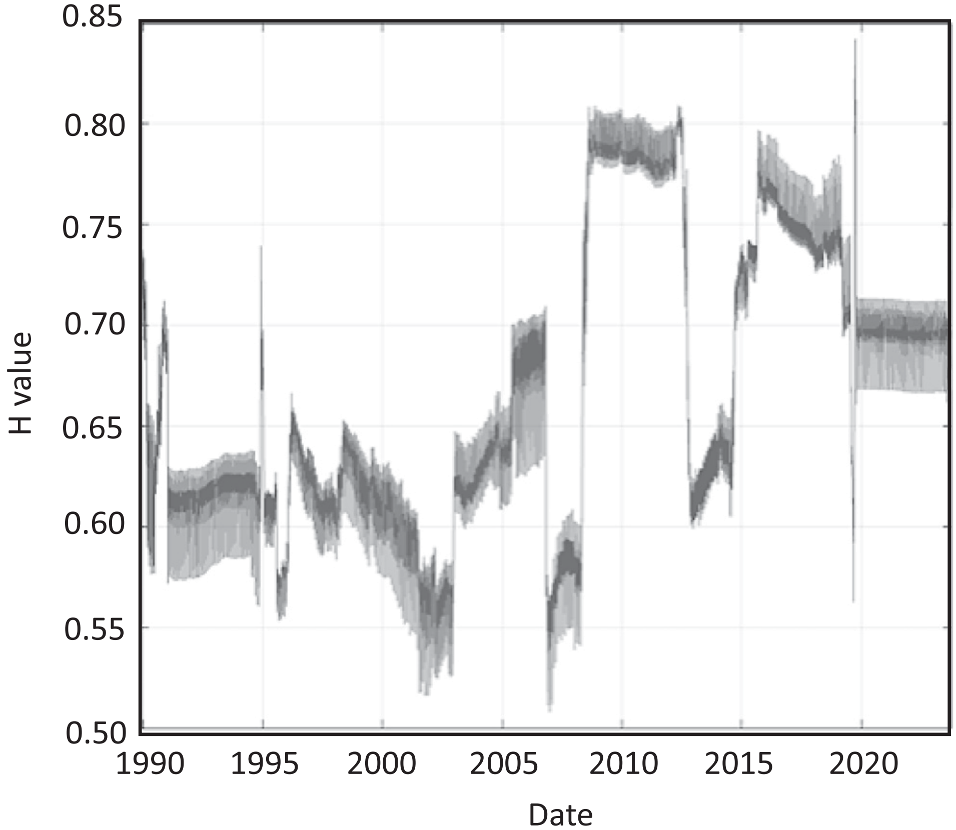


in 1990, when the index fell below 0.5 at the onset of the Gulf War, reflecting heightened uncertainty. As the conflict progressed and conditions stabilized, the Hurst values rose to the range of 0.55–0.60, consistent with persistent price dynamics.

From 1995 to 2005, the Hurst exponents fluctuated near 0.5, suggesting behavior close to a random walk. A sharp decline in 1998 coincided with the Asian financial crisis, highlighting the market's immediate reaction to global shocks. As the crisis unfolded, the Hurst values rebounded above 0.5, before returning to levels near 0.5 in the early 2000s. This stabilization likely reflected the combined influence of increasing financialization of oil markets, early U.S. military action in Iraq, and more coordinated OPEC production policies.

Between 2005 and 2010, the Hurst exponent exhibited a pronounced rise, moving from 0.40 to 0.70. During the 2007–2008 global financial crisis, crude oil

Figure 11
TIME-VARYING *H* VALUE FOR RETURN SQUARE BASED ON AGGREGATED VARIANCE ANALYSIS

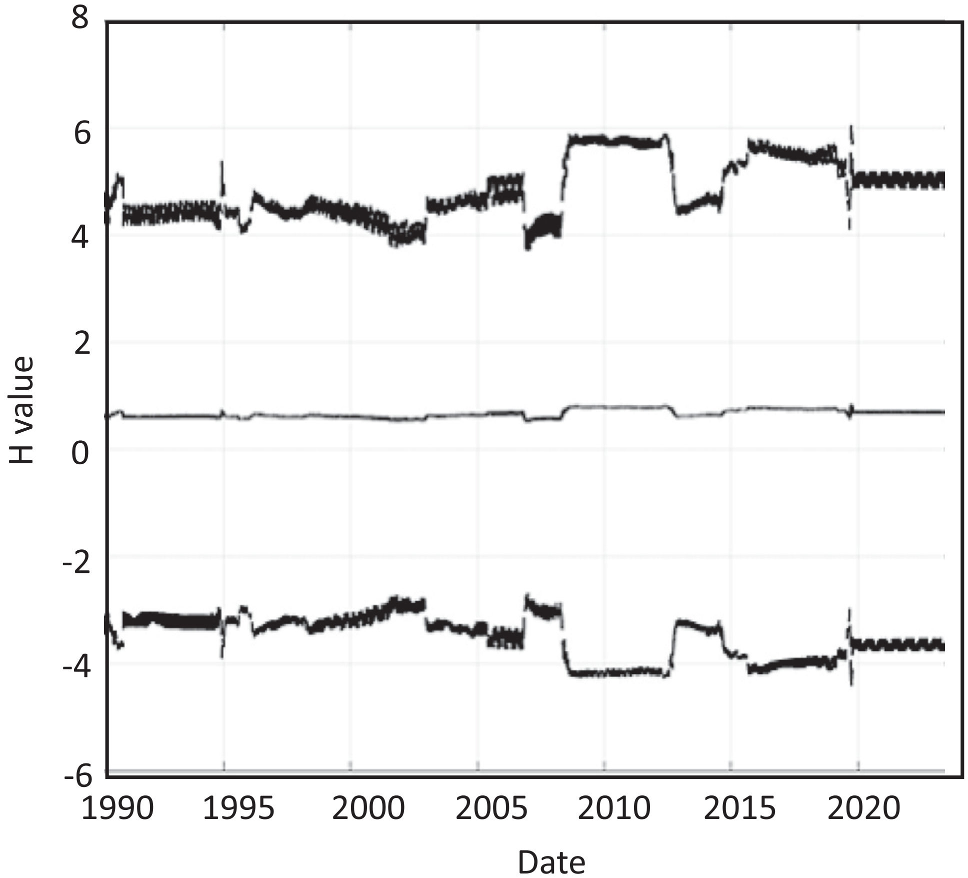


prices collapsed from approximately $147 to $30 per barrel, and efficiency declined sharply, with Hurst values near 0.40. Following the crisis, however, as economic recovery strengthened demand, prices trended upward and the Hurst index rose to 0.70, reflecting persistent long-term dependence.

In 2019, the outbreak of the COVID-19 pandemic triggered another sharp decline in the Hurst exponent. Over time, the index recovered, showing renewed long-term dependence before converging back toward 0.50, consistent with random-walk behavior. Taken together, these fluctuations suggest that while global crises temporarily disrupt efficiency, the WTI market ultimately tends to revert toward weak-form efficiency over time.

Figure 10 presents the time-varying Hurst exponents estimated using the periodogram method with a moving window of 1,000 observations and 95% confidence

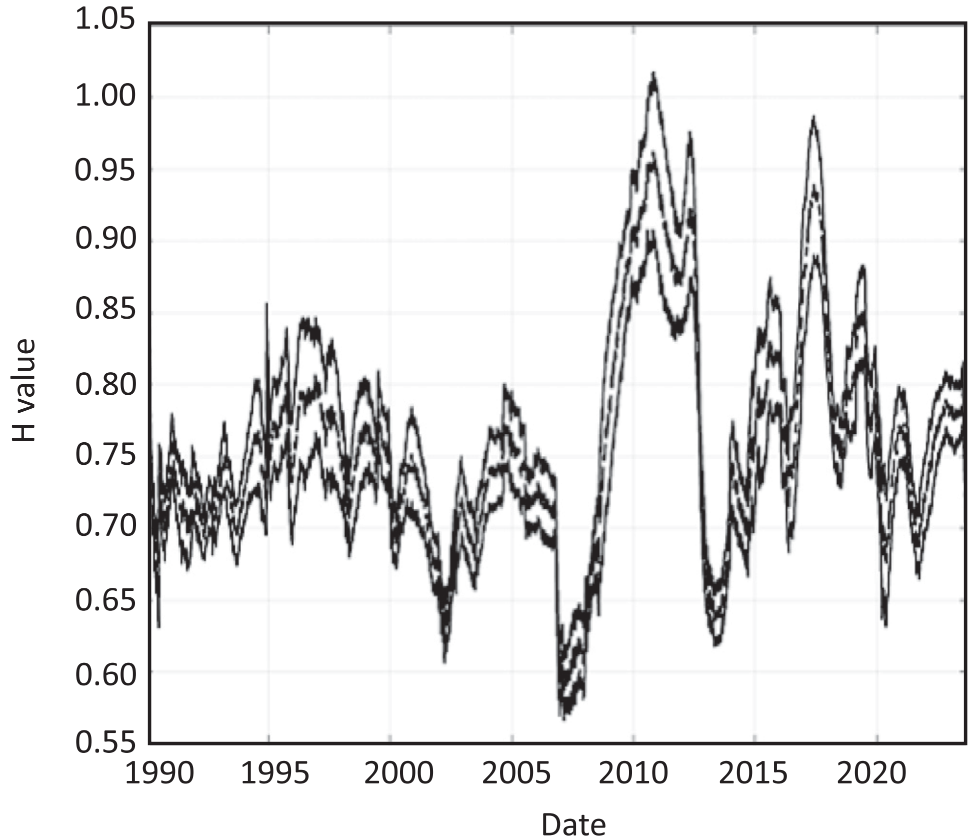
Figure 12
TIME-VARYING *H* VALUE FOR RETURN SQUARE BASED ON AGGREGATED VARIANCE WITH 95% CONFIDENCE INTERVAL



intervals. The exponents fluctuate within a relatively narrow band, ranging from 0.46 to 0.52. Notably, significant declines are observed in 1990, 1995, 1998, 2003, 2007, and 2020—periods that coincide with major geopolitical or economic shocks. These results closely mirror the patterns reported in Figure 7.

Following each of these crises, the Hurst exponents recover rapidly before stabilizing within a narrower range. This behavior reflects the dynamics of investor composition under different market conditions. In normal periods, markets are characterized by a heterogeneous mix of short-, medium-, and long-term participants, with rational investors distributed relatively evenly across investment horizons. However, during crises, sharp price declines and elevated selling pressures often lead long-term investors to shorten their horizons, effectively joining

Figure 13
TIME-VARYING *H* VALUE FOR RETURN SQUARE BASED ON RESCALED RANGE ANALYSIS WITH 95% CONFIDENCE INTERVAL

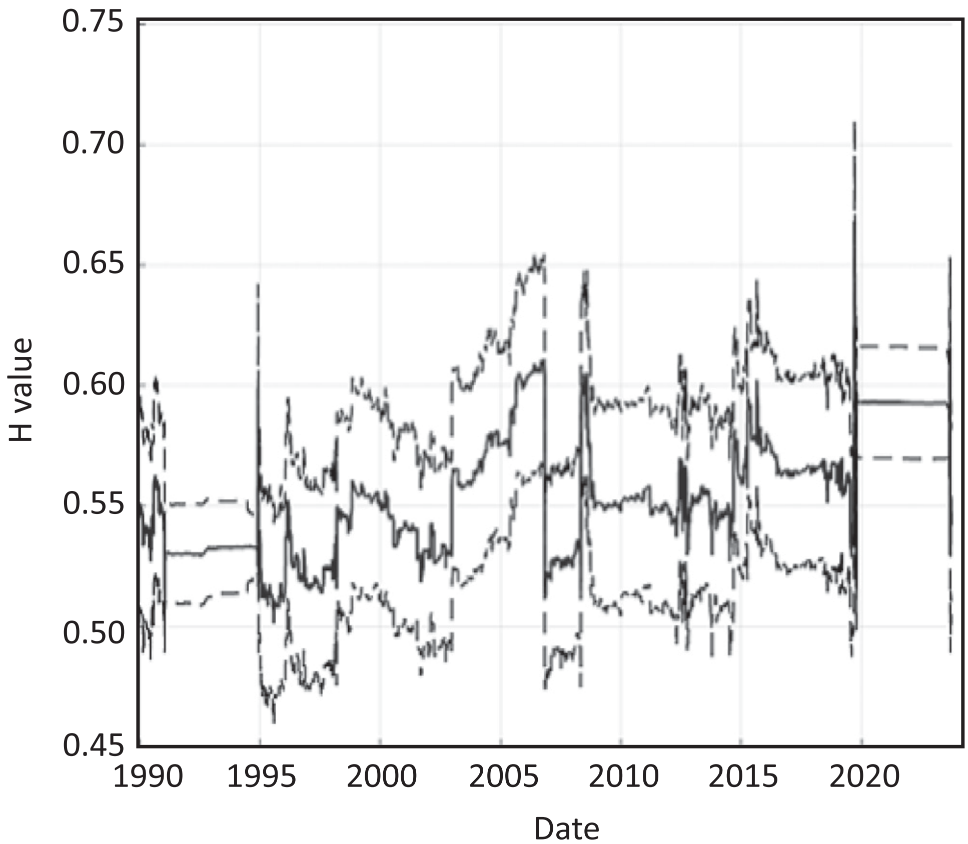


short-term traders. This collective shift induces stronger dependencies in both return and volatility dynamics.

Taken together, the evidence from Figures 7, 9, and 10 suggests that a series which typically resembles random behavior may temporarily transition into a long-range dependent process during periods of crisis. These temporary deviations imply that while the WTI crude oil market broadly aligns with weak-form efficiency under normal conditions, efficiency is significantly weakened during times of geopolitical and economic shocks.

Figure 11 reports the time-varying Hurst exponents for volatility, estimated using the aggregated variance method with moving windows of fixed length. The corresponding 95% confidence intervals are presented in Figure 12. The results clearly indicate that all Hurst values for volatility exceed 0.5, fluctuating

Figure 14
TIME-VARYING *H* VALUE FOR RETURN SQUARE BASED ON PERIODOGRAM ANALYSIS WITH 95% CONFIDENCE INTERVAL



between 0.51 and 0.82, which provides strong evidence of long memory in the volatility series. Notably, this range encompasses the Hurst value for squared returns reported earlier in Figure 2.

We also find that the Hurst values for volatility exhibit substantial shifts during major events. In particular, pronounced changes are observed in 1990, 2002–2003, 2007–2008, and 2019–2020 (see Figure 12).

In Figure 13, the Hurst exponents for return squares deviate significantly from 0.5, indicating the presence of long-term memory. Between 1990 and 2005, the Hurst index remained relatively stable, fluctuating within a narrow range of 0.7 to 0.8. From 2005 to 2020, however, the index exhibited more pronounced variability: it rose sharply between 2005 and 2010, then dropped abruptly from 2010 to

2012, before stabilizing at a relatively steady level of volatility. After 2020, the values fluctuated within a tighter band around 0.8. This range is consistent with the Hurst values for return squares reported in Figure 4.

In Figure 14, the Hurst index lies between 0.5 and 0.6, suggesting the presence of long memory as estimated using the periodogram method. This interval also encompasses the Hurst values for return squares presented in Figure 6.

4. Conclusion

This study estimated the Hurst index using multiple methods—R/S analysis, the aggregated variance method, and the periodogram—to evaluate the dynamic information efficiency of the WTI crude oil market between January 2, 1986, and May 13, 2024. Overall, the results from the three approaches were broadly consistent. The Hurst exponents for returns clustered around 0.5, suggesting that long memory properties are largely absent and that WTI returns generally exhibit weak-form efficiency.

Time-varying analysis using a moving window revealed that episodes of long memory in returns appeared only intermittently, primarily during or following major global events such as the Gulf War, the COVID-19 pandemic, and the Russia-Ukraine conflict. For most periods, however, the aggregated variance and periodogram methods showed no persistent long memory. In contrast, the R/S analysis indicated weak evidence of long memory in returns. Taken together, these findings suggest that WTI returns are better characterized as following a random walk, with temporary deviations during times of crisis.

For volatility, by contrast, all three methods consistently showed strong long memory, as reflected in Hurst values significantly greater than 0.5.

REFERENCES

Akdi, Y., S. Varlik, and H. Berument. 2023. "The Long-Run Relationship Between the Prices of WTI and Brent Crude Oils: Periodogram-Based Cointegration Analyses." *Energy Economics Letters* 10 (1): 35–43. https://doi.org/10.55493/5049.v10i1.4715.

Alvarez-Ramirez, J., J. Alvarez, and E. Rodriguez. 2008. "Short-Term Predictability of Crude Oil Markets: A Detrended Fluctuation Analysis Approach." *Energy Economics* 30 (5): 2645–56. https://doi.org/10.1016/j.eneco.2008.05.006.

Alvarez-Ramirez, J., M. Cisneros, C. Ibarra-Valdez, and A. Soriano. 2002. "Multifractal Hurst Analysis of Crude Oil Prices." *Physica A: Statistical Mechanics and Its Applications* 313 (3–4): 651–70. https://doi.org/10.1016/S0378-4371(02)00985-8.

Chatziantoniou, I., M. Filippidis, G. Filis, and D. Gabauer. 2021. "A Closer Look into the Global Determinants of Oil Price Volatility." *Energy Economics* 95: 105092. https://doi.org/10.1016/j.eneco.2020.105092.

Fernandez, V. 2010. "Commodity Futures and Market Efficiency: A Fractional Integrated Approach." *Resources Policy* 35 (4): 276–82.

Grech, D., and Z. Mazur. 2004. “Can One Make Any Crash Prediction in Finance Using the Local Hurst Exponent Idea?” *Physica A: Statistical Mechanics and Its Applications* 336 (1): 133–45. https://doi.org/10.48550/arXiv.cond-mat/0311627.

Guo, J., Z. Zhao, J. Sun, and S. Sun. 2022. “Multi-Perspective Crude Oil Price Forecasting with a New Decomposition-Ensemble Framework.” *Resources Policy* 77: 102737. https://doi.org/10.1016/j.resourpol.2022.102737.

He, L.-Y., and W.-B. Qian. 2012. “A Monte Carlo Simulation to the Performance of the R/S and V/S Methods—Statistical Revisit and Real-World Application.” *Physica A: Statistical Mechanics and Its Applications* 391 (14): 3770–82. https://doi.org/10.1016/j.physa.2012.02.028.

Hurst, H. E. 1951. “Long-Term Storage Capacity of Reservoirs.” *Transactions of the American Society of Civil Engineers* 116 (1): 770–99. https://doi.org/10.1061/TACEAT.0006518.

Kristoufek, L. 2019. “Are the Crude Oil Markets Really Becoming More Efficient Over Time? Some New Evidence.” *Energy Economics* 82: 253–63. https://doi.org/10.1016/j.eneco.2018.03.019.

Mandelbrot, B. 1972. “Statistical Methodology for Nonperiodic Cycles: From the Covariance to R/S Analysis.” In *Annals of Economic and Social Measurement* 1: 259–90. Stanford, CA: National Bureau of Economic Research.

Mensi, W., C. Aloui, M. Hamdi, and D. K. Nguyen. 2012. “Crude Oil Market Efficiency: An Empirical Investigation via the Shannon Entropy.” *International Economics* 129: 119–37. https://doi.org/10.3917/ecoi.129.0119.

Narayan, P. K., S. Narayan, and X. Zheng. 2010. “Gold and Oil Futures Markets: Are Markets Efficient?” *Applied Energy* 87 (10): 3299–3303. https://doi.org/10.1016/j.apenergy.2010.03.020.

Oberndorfer, U. 2009. “Energy Prices, Volatility, and the Stock Market: Evidence from the Eurozone.” *Energy Policy* 37 (12): 5787–95. https://doi.org/10.1016/j.enpol.2009.08.043.

Tabak, B. M., and D. O. Cajueiro. 2007. “Are the Crude Oil Markets Becoming Weakly Efficient Over Time? A Test for Time-Varying Long-Range Dependence in Prices and Volatility.” *Energy Economics* 29 (1): 28–36. https://doi.org/10.1016/j.eneco.2006.06.007.

Wang, Y., and L. Liu. 2010. “Is WTI Crude Oil Market Becoming Weakly Efficient Over Time? New Evidence from Multiscale Analysis Based on Detrended Fluctuation Analysis.” *Energy Economics* 32 (5): 987–92. https://doi.org/10.1016/j.eneco.2009.12.001.

Wang, Y., and C. Wu. 2012. “Long Memory in Energy Futures Markets: Further Evidence.” *Resources Policy* 37 (3): 261–72. https://doi.org/10.1016/j.resourpol.2012.05.002.

Wang, Y., and C. Wu. 2013. “Efficiency of Crude Oil Futures Markets: New Evidence from Multifractal Detrending Moving Average Analysis.” *Computational Economics* 42 (4): 393–414. https://doi.org/10.1007/s10614-012-9347-6.

Yu, H., G. V. Nartea, C. Gan, and L. J. Yao. 2013. “Predictive Ability and Profitability of Simple Technical Trading Rules: Recent Evidence from Southeast Asian Stock Markets.” *International Review of Economics & Finance* 25: 356–71. https://doi.org/10.1016/j.iref.2012.07.016.