MACROECONOMIC TREND DOMINANCE: A MULTIRESOLUTION (MODWT) ANALYSIS OF THE BET INDEX

Marius Cristian Acatrinei[1*], Alexandru Petrescu[2]
[1), 2)] *Financial Supervisory Authority, Bucharest, Romania*

Abstract
This paper applies multiresolution analysis based on the Maximal Overlap Discrete Wavelet Transform (MODWT) to investigate the structural dynamics of the BET index from the perspective of systemic risk and capital market dynamics in Romania. Using a six-scale decomposition of daily prices over the period 2024–2025, total variability is separated into two fundamental components: the long-term macroeconomic trend (horizons above 64 days) and cyclical oscillations over short and medium horizons (2–64 days).
The empirical results for 2025 indicate an overwhelming dominance of macroeconomic factors, with the trend component explaining 99.15% of total variance, while cyclical oscillations contribute only 0.85%. Within the cyclical component, a clear hierarchy emerges: medium-term cycles (16–64 days) account for over 73% of cyclical variance, while short-term fluctuations (2–8 days) contribute only 12%.
A visual examination of the decomposition over the 2024–2025 period identifies July 2025 as a period with simultaneous amplification across all time scales, from daily volatility to the macroeconomic trend. This simultaneity of amplifications across different time scales represents a distinct pattern observable in the decomposition, coinciding in time with the implementation of electricity price liberalization. The study demonstrates that the variance structure observed in 2025 has implications for risk modeling, as scenarios focused on short-term volatility capture only a minimal fraction of the total observed variability.

Keywords
MODWT, multiresolution analysis, emerging markets, BET index, wavelet decomposition, variance structure.

JEL Classification
G11, C22, E44

[*] Corresponding author, **Marius Cristian Acatrinei** – marius.acatrinei@asfromania.ro.

Introduction

The Maximal Overlap Discrete Wavelet Transform (MODWT) has established itself as a fundamental technique in the analysis of financial time series due to its ability to decompose complex signals into independent components across multiple time scales. Unlike traditional filtering methods, MODWT provides an orthogonal decomposition, a property that implies that the sum of all components exactly reconstructs the original signal, allowing for a precise attribution of variability to each time horizon.

The specialized literature consistently highlights the superiority of MODWT over other wavelet transforms in the analysis of financial time series. According to Ghosh and Chaudhuri (2017), the main advantage is translation invariance, meaning that temporal shifts in the series do not alter the shape of the extracted components, an essential feature for financial data characterized by sudden shocks and unstructured seasonality. Unlike the classical discrete wavelet transform (DWT), MODWT does not require the length of the series to be a power of two, providing full flexibility in the analysis of real-world data (Ismail et al., 2016).

1. **Review of the scientific literature**

In the context of emerging markets, Taştan and Çekiç (2023) investigated the relationship between MSCI indices and the U.S. market using MODWT decomposition for cross-correlation analysis across multiple time scales. An important direction in the recent literature is the integration of MODWT with other statistical models. Alenezy et al. (2023) combine MODWT with fuzzy models for volatility prediction, while Ismail et al. (2016) demonstrate that MODWT-GARCH models provide superior volatility estimates compared to standard GARCH models. Ghosh and Chaudhuri (2017) integrated MODWT into a machine learning framework for exchange rate forecasting, extracting multi-scale features relevant for predictive algorithms. Wen et al. (2022) used MODWT together with quantile regression to analyze risk contagion among international energy, commodity, and equity markets, demonstrating the usefulness of frequency-based risk transmission analysis.

This paper extends the existing literature by applying MODWT to the structural analysis of a European emerging market, with a focus on clearly differentiating between long-term macroeconomic variability and cyclical trading structures. The study introduces a dual methodology for reporting variance contributions, both absolute and relative, providing a more nuanced perspective on the hierarchy of risk sources. The analysis combines quantitative data for the year 2025 with visual observations from the decomposition over the 2024–2025 period, allowing for the identification of distinctive dynamics in the evolution of components across different time scales.

2. **Research methodology**

2.1 MODWT Decomposition

Multiresolution analysis based on MODWT decomposes the observed signal—in this case, the BET stock index—into a set of independent (orthogonal) components that capture oscillations at different time horizons. For a discrete series X_t observed at N equally spaced time points, MODWT produces an additive decomposition of the form:

$$X_t = \sum_{j=1}^{J} \mathcal{D}_j(t) + \mathcal{S}_J(t), t = 1,2, \dots, N$$

where $\mathcal{D}_j(t)$represents the detail coefficients at scale j, capturing fluctuations with periods in the interval $\tau_j \in [2^j \Delta t, 2^{j+1} \Delta t)$, and $\mathcal{S}_J(t)$ denotes the trend component at horizons $\geq 2^J \Delta t$. Here, Δt is the sampling interval (1 day for daily data) and $J$is the maximum decomposition level.

The detail components $\mathcal{D}_j(t)$ are reconstructed from the MODWT wavelet coefficients $\widetilde{W}_{j,t}$by applying the synthesis filters:

$$\mathcal{D}_j(t) = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} \cdot \widetilde{W}_{j,(t-l) \, mod \, N}$$

where $\tilde{h}_{j,l}$ denotes the synthesis wavelet filter at level j and L_j is the effective filter length. Similarly, the smooth (scaling) component is obtained from the scaling coefficients:

$$\mathcal{S}_J(t) = \sum_{l=0}^{L_J-1} \tilde{g}_{J,l} \cdot \tilde{V}_{J,(t-l) \, mod \, N}$$

2.2 Time Scale Interpretation

According to Percival and Walden (2000), each decomposition level $j$is associated with a characteristic time scale given by $\tau_j = 2^j \cdot \Delta t$. For daily financial data ($\Delta t = 1$ day), the empirical coverage of each component is approximately $[2^j, 2^{j+1})$days. Table 1 shows the correspondence between the technical decomposition levels and the relevant time horizons for capital market analysis.

Table no. 1. MODWT decomposition levels and temporal interpretation

Level	Component	Time Interval	Economic Horizon
j=1	$\mathcal{D}_1(t)$	2–4 days	Daily fluctuations
j=2	$\mathcal{D}_2(t)$	4–8 days	Weekly cycles
j=3	$\mathcal{D}_3(t)$	8–16 days	Bi-weekly oscillations
j=4	$\mathcal{D}_4(t)$	16–32 days	Monthly cycle
j=5	$\mathcal{D}_5(t)$	32–64 days	Bi-monthly cycle
J=5	$\mathcal{S}_5(t)$	≥ 64 days	Macroeconomic trend

Source: adapted from Percival and Walden (2000)

The components $\mathcal{D}_1 - \mathcal{D}_5$ capture cyclical oscillations around the long-term trend, while $\mathcal{S}_5$ represents the persistent evolution of the index over horizons longer than two months. The first component, $\mathcal{D}_1$, captures movements over 2–4 days, representing very short-term variability. Component $\mathcal{D}_2$, covering the 4–8 day interval, reflects repetitive cyclical structures within the trading week. Component $\mathcal{D}_3$, covering 8–16 days, captures oscillations over 2–3 weeks. Component $\mathcal{D}_4$, corresponding to the 16–32 day interval, represents the monthly trading cycle. Component $\mathcal{D}_5$, covering 32–64 days, reflects oscillations over 1–2 month horizons. Finally, the component $\mathcal{S}_5$ represents movements over horizons greater than 64 days, capturing the market's underlying trend driven by macroeconomic factors.

2.3 Variance Decomposition

The orthogonality property of MODWT ensures that the total variance of the observed series can be expressed as an exact sum:

$$\sigma^2(X) = \sum_{j=1}^{J} \sigma^2(\mathcal{D}_j) + \sigma^2(\mathcal{S}_J)$$

where $\sigma^2(\cdot)$ denotes the unbiased variance estimator, calculated as:

$$\sigma^2(Y) = \frac{1}{N-1}\sum_{t=1}^{N}(Y_t - \bar{Y})^2$$

This decomposition allows for two complementary analytical perspectives.

The first perspective involves computing the absolute contributions to the total variance, defined as:

$$\text{Absolute contribution}_j = \frac{\sigma^2(\mathcal{D}_j)}{\sigma^2(X)} \times 100\%$$

This perspective answers the question: *how much of the overall movement of the BET index is explained by oscillations at scale j ?* Its utility lies in identifying the dominant factor of total variability, allowing a distinction between trend dominance and cycle contribution.

The second perspective focuses on relative contributions within the cyclical component. First, the cyclical variance is defined as the sum of the variances of all oscillatory components:

$$\sigma^2_{\text{cyclic}} = \sum_{j=1}^{J} \sigma^2(\mathcal{D}_j)$$

Then the relative contributions are computed as:

$$\text{Relative contribution}_j = \frac{\sigma^2(\mathcal{D}_j)}{\sigma^2_{\text{cyclic}}} \times 100\%$$

This perspective answers the question: *within cyclical variability (excluding the macro trend), how important is the cycle at scale j ?* Its usefulness lies in identifying the hierarchy of oscillations across different time horizons.

Both perspectives are necessary for a complete analysis. The absolute perspective shows what dominates the market overall, while the relative perspective reveals the internal structure of the oscillations. For example, the total cyclical component may contribute only 1% of the total variance (absolute perspective), but within this 1%, the monthly cycle may account for 40% of the cyclical variance (relative perspective), indicating a clear hierarchy of oscillations across different horizons.

2.4 Economic Interpretation and Implications

The variance distribution across components provides information about market structure. A market with large contributions from daily and weekly components to cyclical variance would indicate intense activity over very short horizons. A market dominated by the monthly component within cyclical variance would suggest regular mechanisms operating on a monthly horizon. When the trend component dominates the absolute total variance, the market is driven by long-term factors rather than by cyclical oscillations.

From a prudential perspective, an amplification of the monthly component above historical levels may signal the accumulation of pressures over monthly horizons. Simultaneous amplification across all cyclical components plus the trend component represents a distinct cyclical movement propagating across all time scales. Sudden inflections in the trend component may indicate transitions in the long-term evolution of the index.

Data and Implementation

2.3. Sample and Analysis Period

The analysis uses daily closing prices of the BET index from January 4, 2024, to December 31, 2025. The data were obtained from the Bucharest Stock Exchange and verified for consistency. For quantitative variance analysis, the study focuses on the year 2025, which comprises 252 trading days. Visual observations from the decomposition cover the entire period from January 2024 to December 2025, allowing identification of cyclical periods and those with distinctive amplitudes.

3.2 Technical Parameters of the Decomposition

A MODWT decomposition was applied with the following parameters: Daubechies db2 wavelet family with two vanishing moments, filter length L=4, and five decomposition levels (J=5). The choice of the Daubechies db2 wavelet provides an optimal balance between regularity and compact support and is widely used in the literature for similar analyses. The decomposition can be synthetically expressed as:

$$\text{BET}_t = \mathcal{D}_1(t) + \mathcal{D}_2(t) + \mathcal{D}_3(t) + \mathcal{D}_4(t) + \mathcal{D}_5(t) + \mathcal{S}_5(t)$$

This scale-wise partitioning aligns with empirically observed repetitive cyclical structures established in financial econometrics (Ramsey & Lampart, 1998; Gençay et al., 2001).

3. Results and discussions

3.1 Variance Decomposition

Figure 1 presents the complete decomposition of the BET index over the last two years into six independent components. Each panel shows the temporal evolution of a single component, allowing visual identification of periods of amplification or attenuation across different scales. Visual analysis of the decomposition reveals several aspects of the index's dynamics over this period.

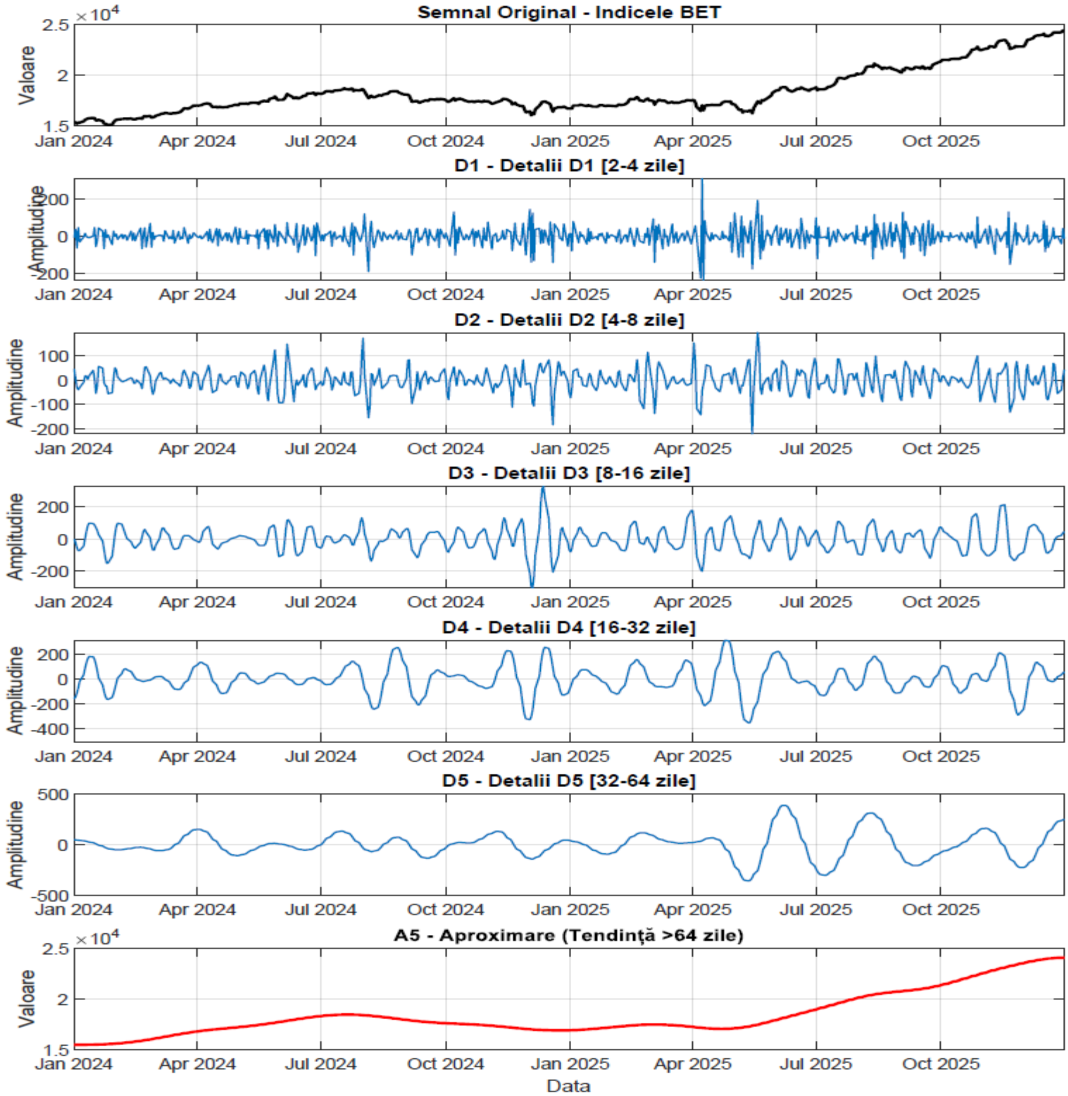

Figure no. 1: MODWT decomposition of the BET index (January 2024 – December 2025)

Source: authors calculation

The top panel, showing the original signal, indicates that the BET index exhibits a steady increase over the entire period, with a visible acceleration in the second half of 2025. Components $\mathcal{D}_1$and $\mathcal{D}_2$, capturing daily and weekly oscillations, display relatively constant amplitudes over most of the period, with a notable intensification in July 2025. Component $\mathcal{D}_3$, representing 8–16 day oscillations, shows increased amplitude in the first half of 2025. The monthly cycle, captured by component $\mathcal{D}_4$, exhibits regular oscillations throughout the period, with a visibly higher amplitude in July 2025. Component $\mathcal{D}_5$, reflecting the bi-monthly cycle, reaches a peak amplitude in July 2025, followed by gradual attenuation. The most visually significant aspect is the dominance of component $\mathcal{S}_5$, which captures the macroeconomic trend and closely follows the overall movement of the index, with a more pronounced upward inflection starting in June 2025.

3.2 Quantitative Analysis of Variance Contributions

Table 2 presents the quantitative decomposition of the BET index variance for 2025 using both perspectives: absolute contributions to total variance and relative contributions within the cyclical component. The total variance of the BET index in 2025 is 4,666,270.73, of which the macroeconomic trend component $\mathcal{S}_5$ contributes 4,626,631.70, representing 99.15% of the total. The cyclical components $\mathcal{D}_1$ through $\mathcal{D}_5$ contribute cumulatively 39,639.03, representing 0.85% of the total variance.

Table no. 2. Variance decomposition of the BET index (2025)

Component	Interval	Absolute Variance	% Total	% Cyclical
D1	2–4 days	2,650.37	0.06%	6.7%
D2	4–8 days	2,258.74	0.05%	5.7%
D3	8–16 days	5,740.79	0.12%	14.5%
D4	16–32 days	12,872.61	0.28%	32.5%
D5	32–64 days	16,116.52	0.35%	40.6%
Cyclical Total		39,639.03	**0.85%**	100%
Trend (S5)	≥64 days	4,626,631.70	**99.15%**	
Total		4,666,270.73	100%	

* *Cyclical variance = $\Sigma(\mathcal{D}_1 \ldots \mathcal{D}_5)$ = 39,639.03. The relative percentages show the internal distribution of oscillations across different time horizons.*

Source: onw calculation for 2025

The interpretation of the absolute perspective, shown in the "% of total" column, reveals the extreme dominance of the macroeconomic trend component for 2025. Component S_5explains 99.15% of the total variability of the BET index that year, reflecting an almost complete concentration on long-term factors. In contrast, the cumulative contribution of all cyclical components amounts to only 0.85% of total variance. Breaking down this modest contribution, activity over daily and weekly horizons, captured by components D1–D2, generated a minimal cumulative contribution of 0.11% to total variability, while short- and medium-term oscillations, reflected in components D_3–D5, contributed 0.74% of total variance.

Analysis of the internal distribution of cyclical variance, presented in the "% of cyclical variance" column, reveals a clear hierarchy of oscillations across different time horizons. Excluding the macroeconomic trend component and focusing exclusively on the structure of cyclical oscillations, we observe that the 1–2 month horizon, captured by component D5, dominates with 40.6% of cyclical variance. The monthly cycle, represented by D4, contributes 32.5% of cyclical variance. Oscillations over 8–16 day horizons, captured by D_3, account for 14.5% of cyclical variance, while daily and weekly activity, reflected in components D1and D2, cumulatively represents 12.4% of cyclical variance.

This dual analysis is essential for a complete understanding of market structure in 2025. In absolute terms, the total cyclical component is modest, representing 0.85% of total variance, meaning that oscillations around the trend had a limited impact on the overall movement of the index. However, within this cyclical component, D4and D5together account for 73.1% of cyclical variance, indicating that when the BET market exhibited oscillations around the macroeconomic trend in 2025, these movements were predominantly driven by patterns over 2–8 week horizons, while shorter-horizon activity played only a minor role in the structure of oscillations.

3.3 Temporal Dynamics

To identify structural changes and notable events, visual examination of Figure 1 allows observations of component evolution over the period January 2025 – December 2025. The first three months of 2025 show moderate amplitudes in the cyclical components in the visual decomposition. Components D1–D2, capturing daily and weekly oscillations, exhibit variations without episodes of visibly extreme amplification. Components D_3–D4 show visually reduced amplitudes compared to later periods in 2025. The macroeconomic trend component exhibits a relatively lateral evolution during this period.

The shock from energy price liberalization in July 2025 generated simultaneous amplification across all time scales, from daily volatility to the macroeconomic trend, indicating a systemic event of endogenous nature that fundamentally reset expectations across all trading horizons. This multi-scale propagation distinguishes systemic shocks from transient volatile episodes.

The second quarter of 2025 shows a visible increase in amplitudes across several components. Component D4, capturing the monthly cycle, records visibly higher amplitudes compared to the first months of the year. Component D_3begins to display more pronounced oscillations. The macro trend component gradually rises toward June.

The last three months of 2025 show visual normalization of the cyclical components. Components D1–D2 return to amplitudes comparable to the beginning of the year. Component D4resumes a more regular oscillation rhythm. Component S_5exhibits a sustained upward movement throughout October–December, visually representing the most pronounced relative contribution of the macro trend compared to other quarters of 2025.

Examination of the decomposition over the two years suggests three phases in component evolution: a first phase in the early months of 2025 with moderate amplitudes, a second phase in July 2025 with simultaneous visible amplification across multiple components, and a third phase in the final months of 2025 with normalization of the cyclical components but a visibly dominant macro trend.

Prudential Implications

3.4 Indicators Derived from MODWT Decomposition

The multi-resolution decomposition allows the construction of quantitative monitoring indicators that can be derived directly from the MODWT components.

The first possible indicator is the ratio between the amplitude of component D4and its historical mean calculated over six-month rolling windows. An indicator exceeding two standard deviations from its historical mean could signal deviations from the typical oscillation dynamics at monthly horizons. Constructing this indicator requires continuously calculating amplitudes over rolling windows and comparing them with the historical distribution observed in previous periods.

A second useful indicator consists of detecting simultaneous amplitude increases in at least five out of six components over a short period, for example, five consecutive trading days. The dynamics observed in July 2025, where multiple components exhibited simultaneous amplifications, illustrate the type of configuration such an indicator should detect. Implementation would require daily monitoring of amplitudes for all components and identifying periods when amplifications exceed predefined thresholds on the majority of scales simultaneously.

The third relevant indicator is the first derivative of component S_5calculated over ten-trading-day rolling windows. Changes in sign or sudden slope modifications in this derivative could indicate transitions in the long-term evolution of the index. The calculation would involve estimating the local trend of component S_5on rolling windows and monitoring moments when this trend changes direction or when the rate of change exceeds historically observed values.

3.5. Implications for Modelling and Stress Testing

The variance structure observed in 2025, with dominance of component S_5at 99.15%, has implications for risk modeling and the construction of stress-testing scenarios. Models focusing predominantly on high-frequency volatility, captured by components D1–D2 which cumulatively contributed 0.11% in 2025, would capture only a minimal fraction of the total observed variability. For the BET index in 2025, risk assessment based exclusively on daily or weekly oscillations would dramatically underestimate the actual variability, which is concentrated at long horizons.

Stress-testing scenarios relevant to the structure observed in 2025 should primarily include shocks and macroeconomic scenarios affecting component S_5, representing persistent disturbances over long horizons. Such scenarios could model adverse developments sustained across multiple quarters, as opposed to short-lived volatile episodes that are quickly absorbed. For example, a scenario simulating a gradual but persistent deterioration of macroeconomic fundamentals over six months would be more relevant to the observed structure than a scenario of extreme volatility concentrated over a few days.

Component D4, given its contribution of 32.5% to the cyclical variance, suggests that scenarios affecting monthly-horizon oscillations would also be relevant. Such scenarios could include disruptions to regular patterns over several weeks, even if their impact on total variance is limited to the 0.85% cyclical fraction. Testing could evaluate resilience to disturbances that amplify component D4beyond historically observed amplitudes, examining how such amplifications would affect liquidity or trading mechanisms.

3.6. Supervision based on Decomposition

Implementing a monitoring system based on MODWT decomposition would allow tracking the evolution of variance distribution across time scales, providing a systematic framework for detecting structural changes. Such a system could include rolling calculations of variances for each component over 60-trading-day windows. This calculation would continuously update variance estimates for each of the six components, enabling the identification of periods when the variance distribution deviates from historical patterns.

Visualization could use heat maps of the relative contributions of each component, calculated monthly or quarterly. These visualizations would show the temporal evolution of variance distribution, allowing rapid detection of periods when certain components become more dominant or when the distribution changes significantly. For example, an increase in the relative contribution of component D4compared to its historical contribution would be immediately visible in a heat map as an intensification of the corresponding color for that period and component.

Tracking the ratio of cyclical variance to total variance provides an aggregated indicator of the weight of oscillations relative to the trend. In 2025, this ratio was 0.85%, indicating the extreme dominance of the macroeconomic trend. Monitoring this ratio over rolling windows would allow the detection of periods when oscillations become more pronounced relative to the trend, even if the trend remains the dominant factor. An increase in this ratio from 1% to 3%, for example, would indicate a structural shift in variance distribution, even if the trend continues to explain over 95% of variability.

A relevant direction for further analysis is predictive modelling through the development of MODWT-GARCH models on each component for forecasting conditional volatility across multiple horizons. Such models would first decompose the series via MODWT and then apply separate GARCH models to each component to capture volatility dynamics at each temporal scale. Recombining the forecasts would provide a more accurate prediction of total volatility compared to directly applying a GARCH model to the original series, since each component may exhibit distinct volatility dynamics.

Conclusions

This study applied a multi-resolution analysis based on the Maximal Overlap Discrete Wavelet Transform (MODWT) to structurally investigate the BET index over 2024–2025. The methodology allowed the separation of total variability into independent components across six temporal scales, from daily oscillations to the macroeconomic trend at long horizons, providing a detailed view of the risk sources driving index movements.

The variance decomposition of the BET index for 2025 shows that the macroeconomic trend component, representing horizons above 64 days, explains 99.15% of total variance, while the sum of cyclical components, representing horizons of 2–64 days, contributes only 0.85%. This extreme concentration on the long-term component indicates that the index's variability in 2025 was predominantly driven by factors operating over extended horizons, rather than by cyclical oscillations at short or medium-term scales.

Within the cyclical component, although modest in absolute terms, internal distribution analysis reveals a clear hierarchy. Components on 16–64 day horizons account for 73.1% of cyclical variance, with the 32–64 day component contributing 40.6% and the 16–32 day component contributing 32.5%, while components on shorter horizons under 8 days cumulatively account for 12.4% of cyclical variance. This internal distribution shows that when the BET market exhibited oscillations around the macroeconomic trend in 2025, these movements were predominantly driven by cyclical patterns over multi-week horizons.

MODWT decomposition provides a methodology for monitoring variance structure across multiple time scales, enabling the construction of specific indicators to detect structural changes or distinctive cyclical movements. Indicators derivable from decomposition include the ratio of each component's amplitude to its historical mean over rolling windows, detection of periods with simultaneous amplification across multiple scales, and tracking the evolution of variance distribution between components on rolling windows. Such indicators would allow identification of periods when market structure shifts.

Complementing this with a wavelet coherence analysis applied over the same period and on indices from external markets would allow the assessment of the degree of synchronization of BET movements with regional market developments. Combining the two methodologies would provide insights into the origins of observed dynamics, differentiating between movements synchronized with external markets and movements showing no external synchronization.

References

[1] Alenezy, Abdullah H., et al. "Predicting stock market volatility using modwt with hyfis and fs.hgd models." *Risks* 11.7 (2023): 121.

[2] Daubechies, Ingrid. "Orthonormal bases of compactly supported wavelets." *Communications on Pure and Applied Mathematics* 41.7 (1988): 909-996.

[3] Gençay, R., Selçuk, F., & Whitcher, B. (2001). *An Introduction to Wavelets and Other Filtering Methods in Finance and Economics*. Academic Press.

[4] Ghosh, Indranil, and Tamal Datta Chaudhuri. "Fractal investigation and maximal overlap discrete wavelet transformation (MODWT)-based machine learning framework for forecasting exchange rates." *Studies in Microeconomics* 5.2 (2017): 105-131.

[5] Ismail, Mohd Tahir, Buba Audu, and Mohammed Musa Tumala. "Comparison of forecasting performance between MODWT-GARCH (1, 1) and MODWT-EGARCH (1, 1) models: Evidence from African stock markets." *The Journal of Finance and Data Science* 2.4 (2016): 254-264.

[6] Percival, Donald B., and Andrew T. Walden. *Wavelet Methods for Time Series Analysis*. Vol. 4. Cambridge University Press, 2000.

[7] Percival, Donald P. "On estimation of the wavelet variance." *Biometrika* 82.3 (1995): 619-631.

[8] Ramsey, James B., and Camille Lampart. "The decomposition of economic relationships by time scale using wavelets: expenditure and income." *Studies in Nonlinear Dynamics and Econometrics* 3.1 (1998): 23-42.

[9] Taştan, Buket, and Ayşegül İşcanoğlu Çekiç. "Cross correlations between MSCI emerging markets indices and US stock market index: evidence from MODWT." *Doğuş Üniversitesi Dergisi* 24.1 (2023): 93-112.

[10] Wen, Fenghua, et al. "Multi-scale risk contagion among international oil market, Chinese commodity market and Chinese stock market: A MODWT-Vine quantile regression approach." *Energy Economics* 109 (2022): 105957.