“An integrated momentum strategy based on entropy and behavioral overreaction: Evidence from Vietnam”

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AN INTEGRATED MOMENTUM STRATEGY BASED ON ENTROPY AND BEHAVIORAL OVERREACTION: EVIDENCE FROM VIETNAM

Abstract

The increasing behavioral volatility and informational complexity of emerging stock markets such as Vietnam create a critical need for more advanced analytical approaches to identify reliable momentum signals. This study aims to develop and validate an integrated momentum-based trading strategy specifically designed for the Vietnamese stock market. Using price and trading volume data for all stocks listed on the VNINDEX from January 2015 to February 2025, the methodology combines permutation-based entropy measures to capture short-term structural patterns with a formation–holding period framework to analyze medium- and long-term dynamics through Continuing Overreaction. The empirical results reveal a pronounced structural divergence in momentum behavior across investment horizons. Short-term momentum is persistent and strongly associated with low-complexity price and volume patterns, indicating coordinated behavioral trading and temporary predictability. In contrast, medium- and long-term Continuing Overreaction effects exhibit consistently negative values across various formation and holding horizons, suggesting that excess trading intensity leads to systematic mean reversion rather than sustained momentum. Backtesting over the period from January 2023 to February 2025 demonstrates that the proposed integrated strategy substantially outperforms a passive VNINDEX buy-and-hold benchmark, achieving a Sharpe ratio of 3.96 compared to 0.64 for the market. The superior performance remains robust across alternative portfolio construction settings and reflects improved downside risk control rather than increased return volatility. These findings indicate that integrating entropy-based complexity measures with volume-driven behavioral indicators provides a more effective framework for enhancing risk-adjusted returns in emerging stock markets.

Keywords predictability, nonlinearity, complexity, herding, sentiment, reversal, volume, efficiency

JEL Classification G11, G12, G14, C58

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INTRODUCTION

In recent years, global financial markets have experienced increasing instability driven by macroeconomic shocks, technological change, and the growing influence of behaviorally motivated trading. These developments have weakened the traditional link between rational valuation and price formation, allowing market anomalies such as momentum and continuing overreaction to persist even under conditions of enhanced transparency and faster information diffusion. This persistence raises a fundamental challenge to conventional views of market efficiency.

The Vietnamese stock market represents a particularly informative case of this challenge. With individual investors accounting for a dominant share of trading activity, market dynamics are strongly shaped by herding behavior, sentiment-driven speculation, and feedback trading. Such a structure intensifies price continuation during

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optimistic phases and accelerates reversals when sentiment shifts, suggesting that price dynamics embed complex behavioral and informational patterns beyond those captured by standard return-based models.

These dynamics have become more consequential as Vietnam's stock market has transitioned from frontier to emerging status, a process associated with greater international participation, higher volatility, and stronger expectations of informational efficiency. Yet the continued coexistence of momentum and mean-reverting behavior indicates unresolved tensions between behavioral persistence, market complexity, and the process of price discovery.

The central scientific problem arising from this context concerns how informational irregularities and behavioral continuation interact to generate, sustain, and ultimately reverse momentum in emerging markets undergoing structural transformation. Addressing this problem is essential for advancing the understanding of price dynamics in behaviorally dominated financial systems.

1. LITERATURE REVIEW

The rationale of this literature review is to evaluate how research on market anomalies has evolved from linear equilibrium-based explanations toward non-linear behavioral and complexity-driven frameworks, particularly in emerging economies. To establish a coherent scientific landscape, this review synthesizes approximately fifty seminal and contemporary studies. The discussion progresses along three interconnected lines: the behavioral foundations of momentum persistence, the distinctive dynamics observed in the Vietnamese stock market, and the growing role of informational complexity and sentiment continuation in explaining persistent price patterns. This structure allows us to identify unresolved gaps between traditional return-based theories and modern, behaviorally informed approaches.

Price momentum represents a fundamental challenge to the Efficient Market Hypothesis, which assumes rapid and unbiased incorporation of information into asset prices (Fama, 1970). Extensive empirical evidence documents return continuation across asset classes and international markets, establishing momentum as a persistent global anomaly (Jegadeesh & Titman, 1993; Rouwenhorst, 1999; Moskowitz et al., 2012; Griffin et al., 2003). Although risk-based models interpret momentum as compensation for systematic risk exposures (Fama & French, 1996; Carhart, 1997; Hou et al., 2015), their explanatory power weakens in environments characterized by limited investor attention, information asymmetry, and constrained arbitrage (Chui et al., 2010; Stambaugh & Yuan, 2017; Goyal et al., 2025). Behavioral finance offers a more comprehensive explanation by emphasizing cognitive biases such as overconfidence, self-attribution, and delayed reaction to information (Kahneman & Tversky, 1979; Barberis et al., 1998; Daniel et al., 1998; Shiller, 2003). These biases generate gradual information diffusion and feedback trading, sustaining price trends beyond fundamental values and ultimately leading to reversals (Hong & Stein, 1999; Grinblatt & Han, 2005; Baker & Wurgler, 2006; Long et al., 1990).

Emerging markets provide a natural laboratory for examining these behavioral mechanisms, with Vietnam representing a particularly informative case. High retail investor participation – accounting for approximately 85% of trading activity – combined with persistent informational frictions amplifies herding behavior and speculative feedback (Batten & Vo, 2014; Vo & Phan, 2019). Empirical studies consistently report short-term momentum accompanied by rapid reversals, a pattern often described as behavioral fragility rather than rational price discovery (Hong & Stein, 1999; Jegadeesh & Titman, 2025; De Bondt & Thaler, 1985; Chiang et al., 2021). These dynamics have intensified during Vietnam's transition from frontier to emerging market status, where capital inflows interact with unresolved inefficiencies. The inherent inability of traditional linear frameworks to resolve these contradictions necessitates a shift toward information-theoretic approaches that explicitly model the non-linear structure and evolution of market information.

Entropy-based measures, such as Permutation Entropy and Permutation Transition Entropy, provide robust tools capable of distinguishing stochastic noise from organized behavioral coordination in financial time series (Bandt & Pompe, 2002; Zunino et al., 2009). Empirical applications demonstrate that declining entropy is often associated with increased collective synchronization and enhanced predictability, whereas rising entropy reflects informational disorder and market instability (Zunino et al., 2009; Zhao et al., 2020). In parallel, the Continuing Overreaction framework formalizes the persistence of investor sentiment through volume-weighted measures, highlighting how sustained belief reinforcement drives momentum beyond fundamental valuation (Byun et al., 2016; Baker & Wurgler, 2006; Lee & Swaminathan, 2000). Integrating informational complexity with behavioral continuation thus provides a necessary bridge between psychological explanations and measurable market structure, a synthesis that remains largely unexplored in the Vietnamese context (Zhao et al., 2020; Hong & Stein, 1999). Within this scientific landscape, existing studies tend to examine momentum either through behavioral explanations or through non-linear complexity measures in isolation, leaving limited evidence on how informational structure and sentiment persistence jointly shape momentum dynamics.

In summary, the literature indicates that while behavioral mechanisms explain the psychological origins of momentum, non-linear tools are required to capture the underlying informational structure sustaining these anomalies.

Accordingly, this study examines how informational complexity and behavioral continuation interact to shape momentum and continuing overreaction in the Vietnamese stock market. Based on this objective, the following hypotheses are proposed:

H1: *The Vietnamese stock market exhibits structured short-term momentum patterns detectable through low Permutation Entropy and stable Permutation Transition Entropy.*

H2: *Medium- and long-term momentum strategies based on Continuing Overreaction display significant mean-reverting tendencies as speculative sentiment dissipates.*

H3: *An integrated strategy combining entropy-based complexity measures and behavioral continuation indicators yields superior risk-adjusted returns compared to passive market benchmarks.*

The conceptual framework links informational regularity captured by entropy measures with sentiment persistence captured by the Continuing Overreaction framework, providing a multi-horizon perspective on market predictability.

2. METHOD

The empirical analysis applies both informational and behavioral perspectives to capture market dynamics. Entropy-based indicators quantify the degree of randomness and structure in price and volume movements, while behavioral measures derived from trading activity assess investor persistence and overreaction. Together, these approaches allow for a data-oriented evaluation of market complexity without relying on restrictive theoretical assumptions.

2.1. Entropy-based complexity measures

We employ Permutation Entropy (PE) and Permutation Transition Entropy (PTE) to evaluate time series complexity. Following Bandt and Pompe (2002), the original series $\{x_t\}$ is reconstructed into m-dimensional state vectors:

$$X_t = \{x_t,\ x_t + \tau,\ \ldots,\ x_t + (m-1)\tau\}, \qquad (1)$$

where τ = 1 and m ∈ [2,5] are selected to balance responsiveness and statistical reliability while mitigating finite-sample effects (Zhao et al., 2020). Each vector is mapped to a unique permutation π (X_t) based on ordinal ranking. PE $(H^{PT}{}_m)$ is defined as the Shannon entropy (Shannon, 1948) of the permutation probabilities $P(\pi i)$ (Equations 2-3).

$$P(\pi i) = \frac{\sum_{t=1}^{T-(m-1)\tau} 1\left[\pi(X_t) = \pi_i\right]}{T-(m-1)\tau}, \qquad (2)$$

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$$H^{PE}{}_{m} = -\sum_{i=1}^{m!} P(\pi_i)\log_2\left[P(\pi_i)\right]. \quad (3)$$

To capture dynamic state shifts, we compute PTE by measuring one-step Markov transitions between consecutive permutations (Equations 4-6), providing a measure of system determinism and predictability (Zunino et al., 2009).

While Permutation Entropy measures static complexity, it ignores dynamic shifts between consecutive permutations. To address this, we employ Permutation Transition Entropy, which extends permutation analysis by incorporating transitions between successive permutations. For the series $\{x_t\}$ $t \in Z$, $t \le T$ within (Ω, F, P), each state vector X t ∈ R m has a unique permutation $\pi(X_t) \in \{\pi i \mid i = 1, \ldots, m!\}$. Dynamic complexity is then estimated by measuring permutation changes through a one-step Markov transition approach. Specifically, if the permutation at time t is represented by πi(t) and the permutation at time $t + 1$ is represented by $\pi_j(t + 1)$, the one-step Markov transition probability from permutation $\pi_i(t)$ to its neighboring permutation where $t = 1, T - (m - 1)\tau$ and $i, j = 1, \ldots, m!$ is calculated using the following formula:

$$P\left(\pi_i^t \to \pi_j^{t+1}\right) = \frac{\sum_{t=1}^{T-(m-1)\tau-1} 1\left[\pi(X_t)=\pi_i, \pi(X_{t+1})=\pi_j\right] \Big/ \left[T-(m-1)\tau-1\right]}{\sum_{t=1}^{T-(m-1)\tau} 1\left[\pi(X_t)=\pi_i\right] \Big/ \left[T-(m-1)\tau\right]}, \quad (4)$$

when T is much greater than $(m - 1)\tau$, the transition probability can be rewritten as:

$$P\left(\pi_i^t \to \pi_j^{t+1}\right) = \frac{\sum_{t=1}^{T-(m-1)\tau-1} 1\left[\pi(X_t)=\pi_i, \pi(X_{t+1})=\pi_j\right]}{\sum_{t=1}^{T-(m-1)\tau} 1\left[\pi(X_t)=\pi_i\right]}. \quad (5)$$

The transition probability $P(\pi_j^t \to \pi_j^{t+1})$, represents the conditional probability that one permutation is followed by another in a time series, also written as: $P(\pi_j^t \mid \pi_j^{t+1})$ (Zhao et al., 2020).

When a permutation is often followed by the same one, the system is more deterministic, showing lower dynamic complexity and higher predictability. Permutation Transition Entropy quantifies this by aggregating all possible permutation transitions, offering a measure of dynamic complexity.

$$H^{PTE}{}_{m} = -\sum_{i=1}^{m!}\sum_{j=1}^{m!} P\left(\pi_i^t, \pi_j^{t+1}\right)\log_2\left[P\left(\pi_j^{t+1} \middle| \pi_i^t\right)\right] = H_m\left(\pi_i^t, \pi_j^{(t+1)}\right) - H_m\left(\pi_i^t\right). \quad (6)$$

$H^{PTE}{}_{m}$ refers to Permutation Transition Entropy, where $H_m(\pi_j^t, \pi_j^{t+1})$ represents the joint permutation entropy, and $H^{TE}{}_{m}(\pi_j^t)$ denotes Permutation Entropy. Permutation Transition Entropy measures the information required to describe the subsequent permutation π_j^{t+1} based on the previous permutation π_j^t, with the information expressed in bits (Zhao et al., 2020).

In fact, $H^{PTE}{}_{m}$ is always non-negative. When the time series has low dynamical complexity, Permutation Transition Entropy approaches zero. This typically occurs when the series follows a consistently increasing or decreasing pattern or any other predictable behavior. On the other hand, when the state transitions are entirely random and evenly distributed, Permutation Transition Entropy reaches its maximum value.

In such cases, we have the formula:

$$P\left(\pi_i^t\right) = \frac{1}{m!}, \quad P\left(\pi_j^{(t+1)}\right) = \frac{1}{m!}, \quad P\left(\pi_i^t, \pi_j^{(t+1)}\right) = \frac{1}{(m!)^2}. \quad (7)$$

Hence, the maximum Permutation Transition Entropy is given by:

$$H^{PTE}{}_{m} = 2\log_2(m!). \quad (8)$$

To normalize Permutation Transition Entropy, the following formula is applied:

$$0 \le \frac{H^{PTE}{}_{m}}{2\log_2(m!)} \le 1. \quad (9)$$

The next section discusses specific properties of the Permutation Transition Entropy method.

When m = 2, only two permutations exist: 01 (increasing) and 10 (decreasing). Four transitions are possible: 01 → 01, 01 → 10, 10 → 01, and 10 → 10, where (i) and (iv) indicate no state change, while (ii) and (iii) represent a change. Finite-size effects must also be considered: Permutation Entropy requires $T \ge m!$, but Permutation Transition Entropy needs $T \ge (m!)^2$. Thus, m = 2-5 is recommended for Permutation Transition Entropy. Zhao et al. tested Gaussian white noise of length $T = 10^6$ with m = 2-7. Theoretical Permutation Transition Entropy values, $H^{PTE}{}_{m} = 2\log_2(m!)$, closely matched empirical results for m = 2-5, but deviations appeared at m = 6 and grew at m = 7 due to finite-size effects.

2.2. Algorithmic procedure for entropy estimation and data processing

The study utilizes monthly trading volume for all VNINDEX-listed stocks from January 2015 to February 2025, totaling 139,935 observations. Aggregating data into monthly figures reduces noise and enables a clear assessment of persistent market trends. While entropy-based measures are estimated using daily price and volume series to capture short-term informational complexity, the Continuing Overreaction analysis relies on monthly aggregated data to examine medium- and long-term behavioral dynamics. The entire computation was implemented in Python using custom scripts developed by the authors. The input data and replication files are openly available at Zenodo (Nguyễn Phương, 2025) to ensure transparency and reproducibility.

Algorithmic procedure for Permutation Entropy – Permutation Transition Entropy computation. The estimation process of Permutation Entropy and Permutation Transition Entropy follows the steps below:

1) Preprocessing: Clean and transform daily price and volume data into log-returns and log-volume changes.

2) Embedding: Reconstruct state vectors with $\tau = 1$, $m \in [2,5]$.

3) Ordinal Mapping: Determine permutations $\pi(X_t)$ for all vectors.

4) Probability Estimation: Compute $P(\pi i)$ and transition probabilities $P(\pi_j^{t+1} \mid \pi_j^{t})$

5) Entropy Calculation: Compute normalized PE and PTE for all variables.

For entropy estimation, we use daily return and trading volume data for all VNINDEX-listed stocks over the same sample period, totaling 3,302,825 observations. This dataset was compiled by the authors for the purpose of this study and, to the best of our knowledge, has not been used in prior empirical research. To enhance the robustness of our analysis, we transform the raw return and volume data into log return and log volume change, which is motivated by three main reasons: they stabilize variance, reduce the impact of outliers, and enhance the ability of entropy methods to detect structural changes.

This study interprets Permutation Entropy and Permutation Transition Entropy across four variables: daily returns, daily volume, log returns, and log volume change.

In this study, lower entropy values indicate a higher degree of ordinal pattern regularity and coordinated trading behavior, whereas higher entropy values reflect increased informational randomness and market inefficiency. This interpretation applies consistently to both price returns and trading volume, allowing entropy measures to capture the degree of behavioral synchronization underlying short-term predictability.

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Based on entropy results, the market can be classified into distinct states. When Permutation Transition Entropy rises while Permutation Entropy remains low, the market enters a transition phase, suggesting that momentum is weakening and potential reversals may occur. In contrast, when both Permutation Entropy and Permutation Transition Entropy are high, the market behaves efficiently, showing minimal predictable patterns and limited scope for momentum strategies.

2.3. Continuing overreaction analysis

To evaluate medium- and long-term dynamics, we apply the Continuing Overreaction (CO) framework within a J/K-month momentum structure, where J denotes the formation period, and K represents the holding period. Unlike traditional momentum strategies based on past returns, our approach ranks stocks by their accumulated CO index, derived from trading volume and return interactions during the J-month formation window. Following Byun et al. (2016), this method distinguishes between speculative overreaction and gradual price adjustments.

To get the continuing overreaction values, we first measure the signed volume of stock i in month t, $SV_{i,t,}$ as follows:

$$SV_{i,t} = \begin{cases} Vol_{i,t}, & if\ r_{i,t} > 0 \\ 0, & if\ r_{i,t} = 0 \\ -Vol_{i,t}, & if\ r_{i,t} < 0 \end{cases}, \quad (10)$$

where $Vol_{i,t}$ refers to the trading volume of stock i during month t. It is determined by summing the daily trading volumes of the stock over all trading days within that month, and the monthly return of stock i for month t is denoted as $r_{i,t}$ (Byun et al., 2016).

From the signed volume values, we calculate $CO_{i,t}$ as follows:

$$CO_{i,t} = \frac{\sum_{J=1}^{12} w_J \cdot SV_{i,t-J}}{\left(\sum_{J=1}^{12} Vol_{i,t-J}\right)/12}, \quad (11)$$

where $w_J = (12 - J + 1)$ by the month of $(t - J)$ Byun et al. (2016).

In this approach, a large positive value of CO indicates that investors exhibit greater overconfidence when responding to positive information in the past, while a large negative CO suggests overconfidence in reacting to negative information. Using this measure, a momentum strategy is constructed by ranking individual stocks based on their CO values at the beginning of each month. Stocks are then divided into quintiles, with the top 20% of stocks with the highest CO values forming the winner portfolio and the bottom 20% with the lowest CO values forming the loser portfolio. The continuing overreaction strategy involves taking a long position in the winner portfolio and a short position in the loser portfolio, with both positions weighted equally – held for a period of K months, where K = 3, 6, 9, 12. To determine the momentum profit for a given month, the returns from the winner portfolio are subtracted from the returns of the loser portfolio, then are averaged across K separate positions, specifically from $t - K$ to $t - 1$. The significance of the average returns is then assessed using t-statistics that are adjusted for autocorrelation and heteroskedasticity using Newey and West's standard errors (Newey & West, 1987).

Algorithmic procedure for J/K-month Continuing Overreaction analysis:

1. Ranking: Compute $SV_{i,t}$ and $CO_{i,t}$ to rank stocks into quintile portfolios.

2. Execution: Take an equally weighted long position in winners and short in losers.

3. Holding: Maintain positions over rolling windows of K months.

4. Validation: Assess monthly returns using Newey-West (Newey & West, 1987) adjusted t-statistics.

3. RESULTS

The empirical analysis documents the interaction between informational complexity and price–volume persistence in the Vietnamese equity market. Beyond statistical significance, the results provide economically meaningful evidence on how behavioral persistence embedded in market structure is reflected in return dynamics across time horizons in Vietnam's equity market.

3.1. Analysis of short-term momentum dynamics using permutation entropy

This subsection evaluates the short-term momentum dynamics of the Vietnamese stock market using Permutation Entropy and Permutation Transition Entropy, aiming to identify whether price and volume fluctuations exhibit structural persistence or randomness. The empirical results reveal clear differences in informational complexity between price- and volume-based measures across embedding dimensions, indicating varying degrees of structural persistence.

Permutation Entropy quantifies the randomness of time series data, with higher values reflecting greater disorder. This pattern holds across all data types, confirming that both prices and volume metrics become harder to forecast as more information is considered. Among them, PE_log_volume records the highest entropy values across all dimensions, indicating that log-transformed volume captures the greatest complexity. By contrast, PE_close has the lowest entropy, suggesting raw price movements retain more structure.

PE_log_return and PE_volume show intermediate complexity: log returns are more stationary than raw prices, leading to higher entropy than PE_close but lower than PE_log_volume.

These findings are broadly consistent with the results of Zhao et al. (2020) and Hong et al. (1999), who observed higher entropy in volume-based measures in other emerging markets, reflecting behavioral trading activity and information dispersion. However, the relatively smaller Permutation Entropy– Permutation Transition Entropy divergence in Vietnam implies that market transitions remain more structurally constrained, suggesting semi-persistent behavioral dynamics.

Permutation Transition Entropy values, however, are consistently lower than Permutation Entropy across all dimensions and variables, indicating that while markets display high entropy, their transitions remain relatively structured. This distinction shows that although raw movements

Table 1. Permutation Entropy and Permutation Transition Entropy for VNINDEX at different embedding dimensions (m = 2-5)

Mesure	m = 2	m = 3	m = 4	m = 5
PE_close	0.713376	1.720003	2.847629	4.139069
PE_log_return	0.802069	2.003153	3.419767	4.98849
PE_volume	0.82344	2.060471	3.552293	5.200487
PE_log_volume	0.843285	2.125276	3.624862	5.246221
PTE_close	0.708784	0.982848	1.256011	1.331767
PTE_log_return	0.779404	1.136754	1.395588	1.465327
PTE_volume	0.79651	1.177311	1.445585	1.500468
PTE_log_volume	0.781403	1.130093	1.347687	1.3989

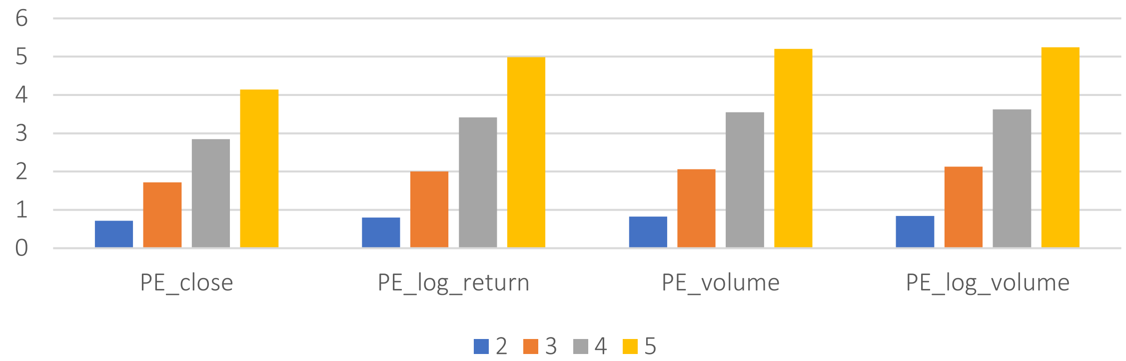

Figure 1. Permutation Entropy of price and volume measures for VNINDEX stocks (m = 2-5, 2015–2025)

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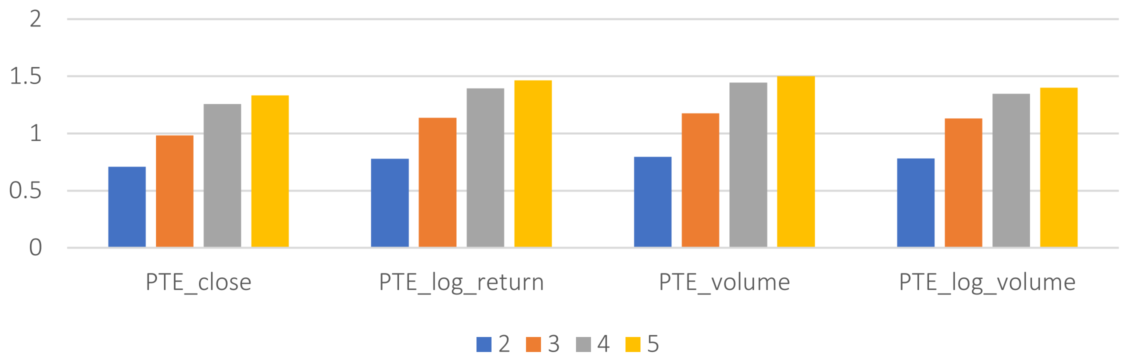

Figure 2. Permutation Transition Entropy of price and volume measures for VNINDEX stocks (*m* = 2-5, 2015–2025)

seem highly random (captured by Permutation Entropy), Permutation Transition Entropy reveals underlying rules in state changes.

Among the measures, PTE_close is the lowest across dimensions, suggesting that price movements follow a more orderly transition than volume-based measures. In contrast, PTE_log_return, PTE_volume, and PTE_log_volume show higher values, indicating that volume-related transformations add more randomness, consistent with the idea that liquidity-driven activity is less predictable than raw prices.

Notably, the gap between Permutation Entropy and Permutation Transition Entropy widens at higher embedding dimensions: Permutation Entropy rises sharply with m, while Permutation Transition Entropy increases more moderately. This implies that even though overall randomness grows with longer histories, transitions remain constrained (Figure 2).

Permutation Entropy rises with embedding dimension, indicating that price and volume series become more unpredictable over longer horizons, consistent with the Efficient Market Hypothesis (EMH) that rapid information incorporation hinders accurate forecasting. Crucially, Permutation Entropy and Permutation Transition Entropy diverge: while Permutation Entropy grows with more historical data, Permutation Transition Entropy – hich captures state-to-state transition dynamics – ains comparatively stable, implying that markets, though apparently random, follow constrained transition rules shaped by investor

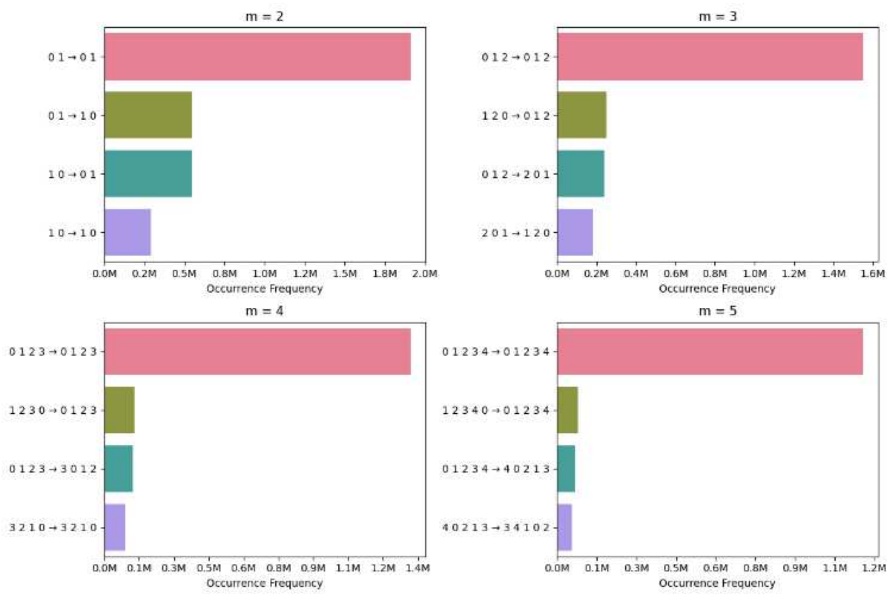

Figure 3. Most frequent permutation transitions of daily closing prices for VNINDEX stocks (m = 2-5, 2015–2025)

sentiment, trading behavior, and liquidity cycles. Volume-based transformations consistently show higher entropy than price-based measures, reflecting the greater complexity of trading activity.

For the simplest case, $m = 2$, the dominant transition is "01 → 01," showing that price increases are likely followed by further increases. Similarly, "10 → 10" confirms persistence in downward trends.

With $m = 3$, "012 → 012" is the most frequent, reinforcing sustained positive trends. Other transitions like "120 → 012" and "012 → 201" show occasional shifts, meaning trends may weaken or reverse after extended runs.

At $m = 4$, "0123 → 0123" dominates, showing that four consecutive increases tend to repeat. Similarly, "3210 → 3210" indicates persistence in downward trends.

For $m = 5$, the main transition is "01234 → 01234," again confirming persistence across longer horizons. Yet, shifts like "01234 → 40213" and "40213 → 34102" suggest greater structural changes.

Overall, the persistence of transitions such as "01→01" and "012→012" confirms that short-term price momentum dominates across multiple embedding dimensions. This indicates that the Vietnamese market retains weak-form inefficiency, where past states influence future price directions.

Figures 4 through 6 extend this analysis to log returns, trading volume, and log-volume changes to verify the robustness of these patterns across alternative data transformations and liquidity dimensions. Across all measures, a consistent structural pattern emerges: sequentially ordered transitions such as '01 → 01', '012 → 012', and '01234 → 01234' dominate across embedding dimensions, indicating persistent short-term momentum. Compared with raw prices, volume-based measures (Figures 5 and 6) exhibit more frequent structural reordering, reflecting the greater behavioral and liquidity-driven complexity of trading activity in the Vietnamese market. Despite these nuances, the stability of ordered transitions across all variables confirms that short-term dynamics are not purely random, thereby rejecting the null hypothesis and providing empirical evidence consistent with *H1*.

3.2. Evaluation of medium- and long-term momentum via the continuing overreaction effect

To assess the medium- and long-term persistence of investor behavior, the Continuing Overreaction framework is applied to J/K-month momentum strategies. This section evaluates whether price adjustments and trading activity display continuation or mean reversion over extended horizons.

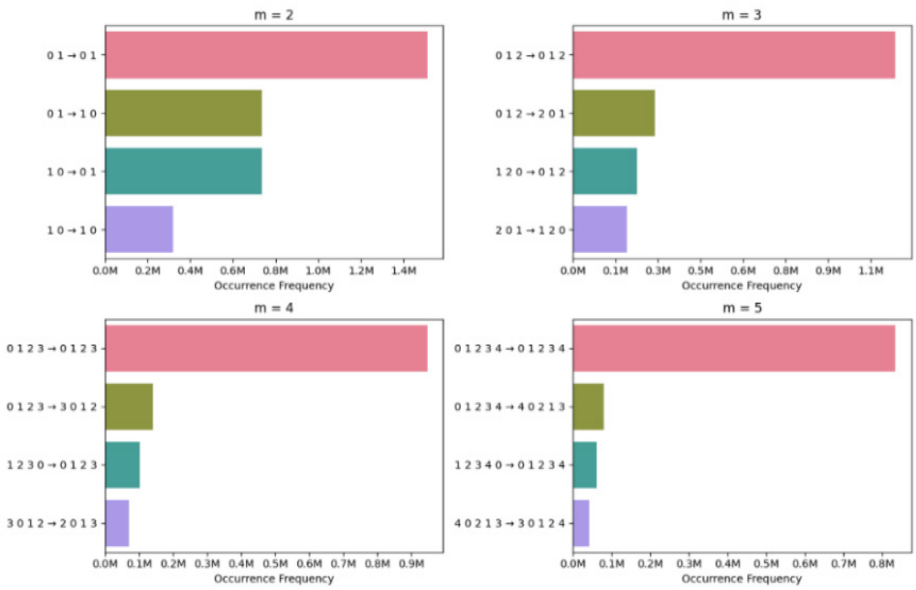

Figure 4. Most frequent permutation transitions of log returns for VNINDEX stocks (m = 2-5, 2015–2025)

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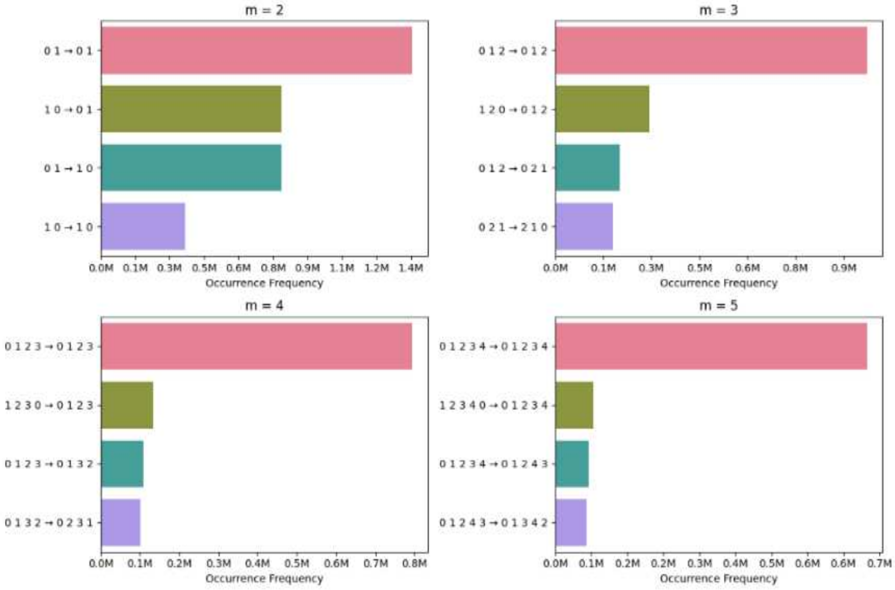

Figure 5. Most frequent permutation transitions of trading volume for VNINDEX stocks (m = 2-5, 2015–2025)

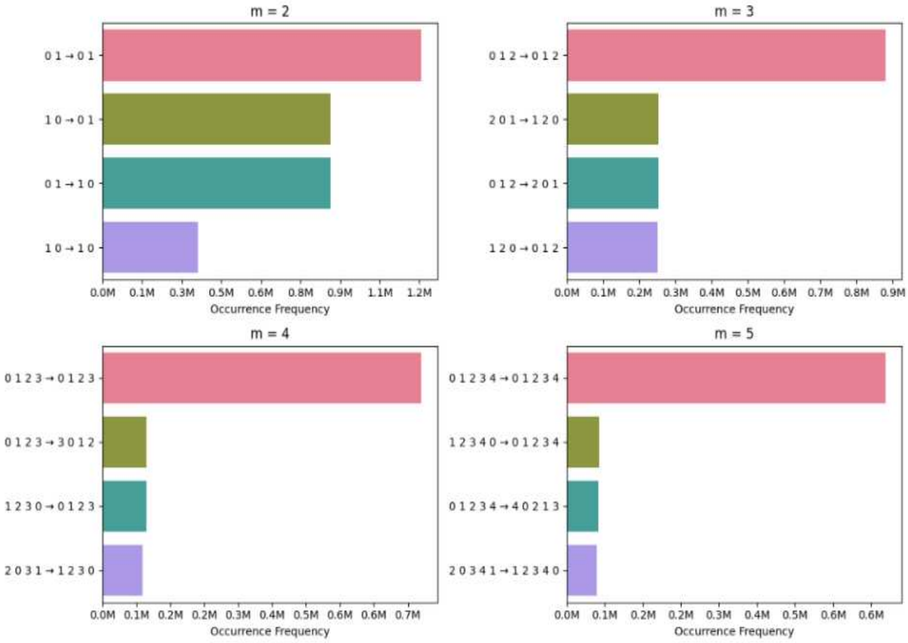

Figure 6. Most frequent permutation transitions of log-volume changes for VNINDEX stocks (m = 2-5, 2015–2025)

While Permutation Entropy and Permutation Transition Entropy offer daily insights into momentum, the J/K month approach examines these effects on a monthly scale. Continuing Overreaction evaluates each J/K strategy, differing from conventional reliance on accumulated returns. The table reports Continuing Overreaction results based on trading volume (Dec 2015 – Feb 2025).

For $J = 3$, CO starts at –0.0247% (K3) with tstat = 1.73843, showing limited significance. At K6, CO declines to –0.0061% while tstat surges to 23.21346. At K9, CO = –0.0043% with tstat = 31.10683, and at K12, CO = –0.0036% with tstat = 39.66041, confirming persistent declines.

For J = 6, CO_K3 = –0.0060% with stronger significance (tstat = 12.96332). At K6, CO falls to

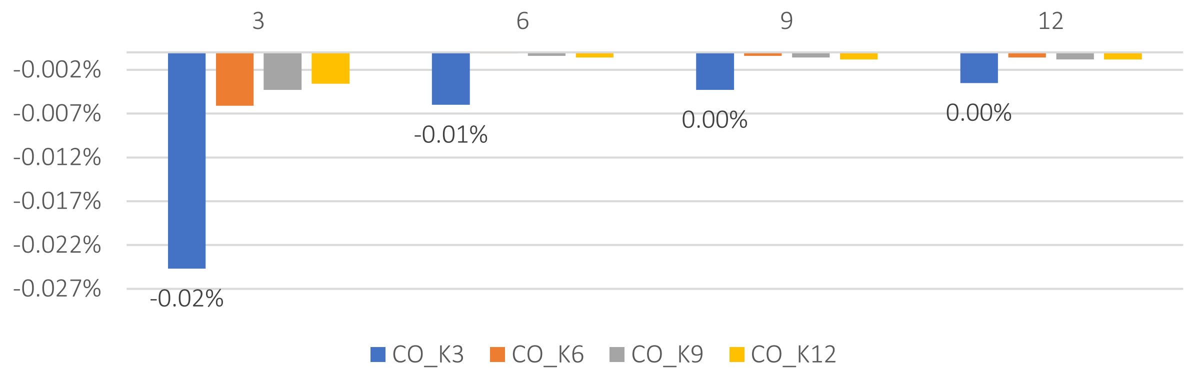

Figure 7. Continuing Overreaction (CO) values of Winner-minus-Loser portfolios across J/K horizons for VNINDEX stocks (2015–2025)

–0.0001% (tstat = 27.94051), then –0.0004% (tstat = 36.75407) at K9, and –0.0006% (tstat = 46.0509) at K12, indicating sustained declines with longer formation periods.

For J = 9, CO_K3 = –0.0043% (tstat = 12.93702). With longer K, CO falls to –0.0004% (K6), –0.0006% (K9), and –0.0008% (K12), with rising tstats of 26.56517, 36.04989, and 45.34236, confirming robustness.

For J = 12, CO_K3 = –0.0035% (tstat = 13.22779). At K6, CO = –0.0006% (tstat = 26.16083), K9 shows CO = –0.0008% (tstat = 35.66111), and K12 remains –0.0008% with tstat = 45.12186.

A consistent feature across all strategies is the negative CO values, indicating that after an initial surge in trading volume, activity declines instead of persisting (Figure 7). Since the CO formula incorporates volume aligned with the monthly return, this effect is closely tied to price movements: positive returns often attract higher volume during formation, but sentiment shifts or capital outflows subsequently reduce activity. The persistence of negative CO values across J/K strategies highlights characteristics of the Vietnamese stock market during 2015–2025.

Economically, the persistent negative Continuing Overreaction values indicate that speculative trading surges in Vietnam dissipate rather than compound over time, leading to systematic momentum decay and predictable price mean-reversion. These results are consistent with *H2*, indicating that medium-term momentum reflects temporary overreaction rather than sustained continuation.

3.3. Backtesting the performance of the integrated model

Finally, the integrated model combining Permutation Entropy, Permutation Transition Entropy, and Continuing Overreaction is validated through backtesting to verify its predictive ability under real-market conditions.

A hybrid strategy incorporating both short-term analyses using Permutation Entropy and Permutation Transition Entropy, and the long-term Continuing Overreaction analysis using the J/K-month momentum framework, is the most advantageous.

The backtest uses Permutation Entropy, Permutation Transition Entropy, and Continuing Overreaction, calculated as described earlier. The

Table 2. Continuing Overreaction results for J/K-month strategies (Dec 2015–Feb 2025)

J	CO_K3	tstat_K3	CO_K6	tstat_K6	CO_K9	tstat_K9	CO_K12	tstat_K12
3	–0.0247%	1.73843	–0.0061%	23.21346	–0.0043%	31.10683	–0.0036%	39.66041
6	–0.0060%	12.96332	–0.0001%	27.94051	–0.0004%	36.75407	–0.0006%	46.0509
9	–0.0043%	12.93702	–0.0004%	26.56517	–0.0006%	36.04989	–0.0008%	45.34236
12	–0.0035%	13.22779	–0.0006%	26.16083	–0.0008%	35.66111	–0.0008%	45.12186

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dataset covers all VNINDEX stocks from January 2023 to February 2025, offering a comprehensive and up-to-date view of strategy effectiveness over both short- and long-term horizons. Log returns are chosen over absolute returns, trading volume, or log-volume change because they capture price dynamics more effectively. Permutation Entropy and Permutation Transition Entropy are imputed with median values, while missing Continuing Overreaction values are set to zero, assuming no evidence of continuing overreaction.

The strategy formation begins with the generation of buy and sell signals.

A long position is taken when both Permutation Entropy and Permutation Transition Entropy fall below their thresholds, indicating a predictable, less chaotic market. Combined with a positive log return, this signals continuation of an upward trend. Low entropy suggests orderly price movements, making momentum more likely.

A short position is triggered when CO is negative, signaling continuing overreaction and a possible reversal. This is reinforced if Permutation Entropy or Permutation Transition Entropy exceeds thresholds, showing higher uncertainty and volatility. In such cases, the strategy expects a downward correction.

If neither condition holds, the strategy stays neutral, avoiding exposure during uncertainty.

The positions are set numerically as follows:

Long position = 1; Neutral position = 0; Short position = –1

Following signal generation, the strategy is subjected to a rigorous backtesting process. Starting with an initial capital of 1,000,000 VND, the portfolio's daily return is calculated based on the log return of the selected stock and the corresponding position (long, short, or neutral). The cumulative portfolio value is updated incrementally using the formula:

$$Portfolio\ Value_t = Portfolio\ Value_{t-1} + Daily\ \mathrm{Re}turn_t. \quad (12)$$

The thresholds for Permutation Entropy and Permutation Transition Entropy are initially set to their median values, representing a baseline level of market behavior. These thresholds are systematically adjusted in increments to explore different market scenarios and evaluate the robustness of the strategy.

Key performance metrics are then computed to evaluate the effectiveness of the strategy.

(i) Cumulative Return measures the total growth of the portfolio over the backtest period, while

(ii) Annualized Return provides a standardized measure for comparing performance across different timeframes.

(iii) Volatility is calculated using the standard deviation of daily returns, offering insights into the strategy's risk exposure. Finally, the

(iv) Sharpe Ratio assesses the risk-adjusted return, representing the efficiency of the strategy in generating returns per unit of risk.

To test the robustness of the strategy, a sensitivity analysis adjusts Permutation Entropy and Permutation Transition Entropy thresholds from their median values across four levels, creating 16 scenarios. This evaluates performance under varying market conditions and identifies the optimal thresholds that maximize returns while keeping risks acceptable, ensuring adaptability across environments.

Each result of the m value reports cumulative return, annualized return, volatility, and Sharpe ratio for different thresholds. Adjustments, denoted by increasing m, refine entry and exit points. Results show that $m = 2$ and $m = 3$ offer the best balance between risk and return.

For $m = 2$, the Sharpe ratio stands at 3.96, which indicates a favorable risk-adjusted return. At this stage, the marginal benefits from increasing m become limited, with diminishing returns. When m = 3 is applied, the lack of volatility escalation indicates that the strategy is still well-managed in terms of downside risk. With $m = 4$, however, cumulative return falls slightly without Sharpe ratio improvement, while volatility remains stable, showing diminishing marginal gains. The same occurs at $m = 5$, with no notable progress.

These results align with prior findings by Bandt and Pompe (2002) and Zhao et al. (2020), showing that low embedding dimensions yield optimal performance by balancing responsiveness with stability.

To evaluate strategy effectiveness, we also backtest VNINDEX (1/2023–2/2025) without applying any strategy, using its Cumulative Return, Annualized Return, Volatility, and Sharpe Ratio as benchmarks. From Jan 2023 to Feb 2025, VNINDEX showed a Cumulative Return of 20.78% and an Annualized Return of 9.60%, reflecting modest growth but with high Volatility (14.97%). The Sharpe Ratio of 0.6412 indicates returns did not sufficiently offset risk, exposing the drawback of passive investment under uncertainty, as buy-and-hold leaves investors vulnerable to market swings and limits risk management.

Table 3. VNINDEX benchmark performance (Jan 2023 – Feb 2025)

Number	Metric	Value
0	Cumulative Return	0.207782
1	Annualized Return	0.095997
2	Volatility	0.149715
3	Sharpe Ratio	0.641200

Note: VNINDEX benchmark performance metrics (Cumulative Return, Annualized Return, Volatility, Sharpe Ratio) for Jan 2023 – Feb 2025.

Economically, the superior Sharpe ratio of 3.96, together with lower volatility relative to the VNINDEX benchmark, indicates that combining informational complexity with behavioral signals improves risk-adjusted performance. Overall, the backtesting results are consistent with H3, confirming that the integrated complexity–behavioral framework outperforms passive investment in risk-adjusted terms.

Overall, the strategy's strong cumulative returns, high Sharpe ratio, and stable volatility establish it as a reliable approach to market momentum. Further adjustments yield limited incremental gains, as higher embedding dimensions do not materially improve risk-adjusted performance. This pattern can be attributed to the model's ability to reduce exposure during periods of elevated informational complexity, as captured by higher entropy values. By combining entropy-based filtering with the behavioral CO measure, the strategy selectively avoids high-noise environments, thereby improving risk-adjusted returns and providing empirical support for *H3*. Its adaptability is another advantage: effectiveness across thresholds shows resilience, while higher m values add little, as stability in volatility and Sharpe ratios confirms effectiveness without extra risk.

4. DISCUSSION

The findings suggest that the Vietnamese stock market exhibits structured momentum dynamics rather than purely random evolution, supporting the presence of short-term persistence (*H1*) and underscoring the role of behavioral forces in shaping price–volume interactions. The observed divergence between Permutation Entropy and Permutation Transition Entropy is consistent with informational inefficiency documented in other emerging markets (Zunino et al., 2009). However, relative to more developed markets such as China (Zhao et al., 2020), Vietnam displays tighter state-to-state constraints in permutation transitions, indicating that trading activity is more strongly driven by recurrent behavioral responses than

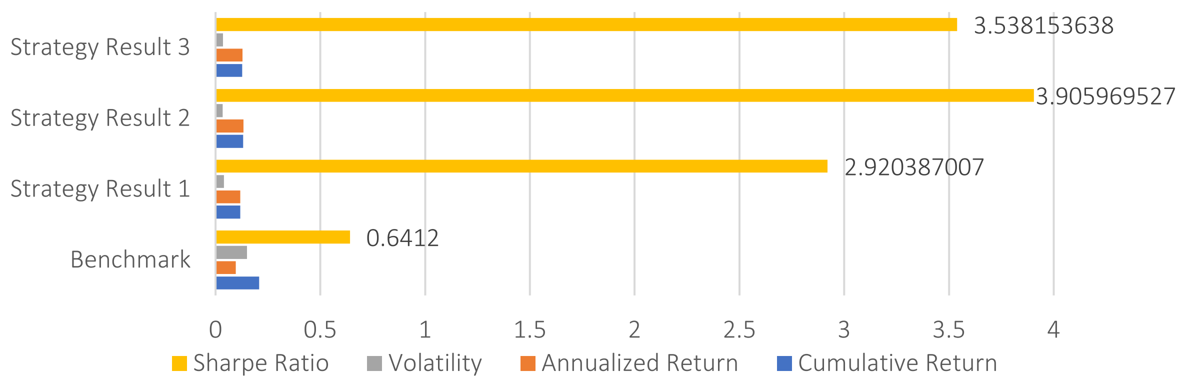

Figure 8. Performance comparison between the VNINDEX benchmark and the integrated strategy (Jan 2023 – Feb 2025)

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by rapidly diffused information processing. This comparison suggests that short-term predictability in Vietnam is not merely a statistical artifact but reflects coordinated trading behavior embedded in market microstructure.

At medium-term horizons, the Continuing Overreaction results (*H2*) reveal a pronounced reversal mechanism. The consistently negative CO values across formation and holding periods contrast with the more persistent momentum documented in other Asian markets (Chui et al., 2010), indicating that speculative momentum in Vietnam tends to dissipate once sentiment-driven trading weakens. This pattern is characteristic of markets where institutional arbitrage remains limited, allowing behavioral corrections and liquidity withdrawal to dominate price adjustment. In this context, medium-term momentum reflects temporary overreaction rather than sustained continuation, leading to systematic mean reversion.

The superior performance of the integrated entropy–behavioral framework (*H3*) further reinforces this behavioral interpretation. The Sharpe ratio of 3.96 achieved at low embedding dimensions is consistent with theories of limited attention (Barberis et al., 1998), which posit that market participants react primarily to recent information, while longer historical depth contributes little incremental forecasting power. Taken together, these findings position Vietnam as a market in which transient short-term behavioral regularities coexist with medium-term correction mechanisms. From a practical perspective, the entropy–Continuing Overreaction framework provides a structured quantitative approach for exploiting short-lived momentum while mitigating exposure to subsequent reversals. Future research may extend this analysis by incorporating direct sentiment measures or institutional indicators to examine how these non-linear dynamics evolve as the market progresses toward greater maturity.

CONCLUSION

The primary objective of this study was to examine how informational complexity and investor overreaction jointly shape momentum dynamics in the Vietnamese equity market. The empirical analysis identifies non-random, structured patterns in short-term price–volume transitions alongside a systematic tendency toward mean reversion at medium-term horizons. In addition, the integrated entropy–behavioral strategy delivers substantial risk-adjusted outperformance, achieving a Sharpe ratio of 3.96 relative to a passive market benchmark. These results indicate that Vietnam's equity market operates under a condition of partial efficiency, where synchronized behavioral dynamics play a central role in momentum formation and correction rather than being fully offset by fundamental arbitrage. Future research may further refine this framework by incorporating sentiment-based or macroeconomic indicators to enhance the understanding of volatility, predictability, and risk management in emerging equity markets.

AUTHOR CONTRIBUTIONS

Conceptualization: Loan Thi Vu, Minh Phuong Nguyen, Quoc Anh Hoang.
Data curation: Minh Phuong Nguyen.
Formal analysis: Loan Thi Vu, Minh Phuong Nguyen.
Investigation: Loan Thi Vu, Quoc Anh Hoang.
Methodology: Loan Thi Vu, Minh Phuong Nguyen, Quoc Anh Hoang.
Software: Minh Phuong Nguyen.
Supervision: Loan Thi Vu.
Validation: Loan Thi Vu.
Visualization: Quoc Anh Hoang.
Writing – original draft: Minh Phuong Nguyen, Quoc Anh Hoang.
Writing – review & editing: Loan Thi Vu.

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APPENDIX A

Table A1. Annual summary of VNINDEX data (2015–2025)

Year	Listed firms	Average trading volume	Average closing price
2015	867	173182.1	8.36528
2016	1007	163234.3	9.613818
2017	1274	193630.5	11.07776
2018	1401	169262.7	11.60865
2019	1463	122146.6	12.18392
2020	1513	249674.1	12.33525
2021	1556	601412.4	17.20984
2022	1581	467812.5	18.81119
2023	1594	510258.9	17.55816
2024	1581	561126.4	20.67931
2025	1336	521561.1	24.4445

Table A2. Backtesting results for integrated Permutation Entropy – Permutation Transition Entropy – Continuing Overreaction model (m = 2)

PE_Threshold	PTE_Threshold	Cumulative Return	Annualized Return	Volatility	Sharpe Ratio
0.676183063	1.183310528	0.027901655	0.028142519	0.051824371	0.543036375
0.676183063	2.183310528	0.046740865	0.046986143	0.050642422	0.927802062
0.676183063	3.183310528	0.046740865	0.046986143	0.050642422	0.927802062
0.676183063	4.183310528	0.046740865	0.046986143	0.050642422	0.927802062
1.676183063	1.183310528	0.044940291	0.045185147	0.052228029	0.865151297
1.676183063	2.183310528	0.132200949	0.132466252	0.033913796	3.905969527
1.676183063	3.183310528	0.132200949	0.132466252	0.033913796	3.905969527
1.676183063	4.183310528	0.132200949	0.132466252	0.033913796	3.905969527

Note: m = 2; Key performance metrics for the backtest with embedding dimension m = 2; bold values denote optimal scenarios.

Table A3. Backtesting results for the integrated model (m = 3)

PE_Threshold	PTE_Threshold	Cumulative Return	Annualized Return	Volatility	Sharpe Ratio
1.682749439	4.685804465	0.031390906	0.031632587	0.052066941	0.607536877
1.682749439	5.685804465	0.04237635	0.042620605	0.052099952	0.818054598
1.682749439	6.685804465	0.042692286	0.042936616	0.052104962	0.824040828
1.682749439	7.685804465	0.042692286	0.042936616	0.052104962	0.824040828
2.682749439	4.685804465	0.044260838	0.044505535	0.05224211	0.851909219
2.682749439	5.685804465	0.111937938	0.112198493	0.042060522	2.667548742
2.682749439	6.685804465	0.132200949	0.132466252	0.033913796	3.905969527
2.682749439	7.685804465	0.132200949	0.132466252	0.033913796	3.905969527

Note: m = 3. Key performance metrics for the backtest with embedding dimension m = 3; bold values denote optimal scenarios.

Table A4. Backtesting results for the integrated model (m = 4)

PE_Threshold	PTE_Threshold	Cumulative Return	Annualized Return	Volatility	Sharpe Ratio
2.717089085	7.39574032	0.032789664	0.033031672	0.052053619	0.634570145
2.717089085	8.39574032	0.039038317	0.03928179	0.052136136	0.753446514
2.717089085	9.39574032	0.041642174	0.041886257	0.052116709	0.803701107
2.717089085	10.39574032	0.042246561	0.042490786	0.052110923	0.815391162
3.717089085	7.39574032	0.043049465	0.043293878	0.052117633	0.830695399
3.717089085	8.39574032	0.067810657	0.068060872	0.050714509	1.342039457
3.717089085	9.39574032	0.095577292	0.095834013	0.046336295	2.068227803
3.717089085	10.39574032	0.11723802	0.117499817	0.040234331	2.920387007

Note: m = 4; Key performance metrics for the backtest with embedding dimension m = 4; bold values denote optimal scenarios.

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Table A5. Backtesting Results for the Integrated Model (m = 5)

PE_Threshold	PTE_Threshold	Cumulative Return	Annualized Return	Volatility	Sharpe Ratio
3.395350762	3.488752698	0.007650205	0.007886323	0.050439236	0.156352942
3.395350762	4.488752698	0.021408042	0.021647384	0.051558867	0.419857639
3.395350762	5.488752698	0.032630645	0.032872616	0.052023075	0.631885294
3.395350762	6.488752698	0.039005841	0.039249307	0.05206083	0.753912426
4.395350762	3.488752698	0.041990951	0.042235116	0.052265022	0.808095241
4.395350762	4.488752698	0.078546748	0.078799479	0.049417886	1.594553828
4.395350762	5.488752698	0.113259778	0.113520643	0.041640985	2.726175762
4.395350762	6.488752698	0.12759791	0.127862135	0.036138096	3.538153638

Note: m = 5; Key performance metrics for the backtest with embedding dimension m = 5; bold values denote optimal scenarios.

Table A6. Descriptive statistics for VNINDEX benchmark data (Jan 2023–Feb 2025)

Statistic	Time	Close	Volume	Daily return
Count	519	519	519	518
Mean	1/22/2024 4:34	1,183.524066	767,406,156	0.000409239
Min	1/5/2023 0:00	1,021.25	336,332,868	–0.04699201
25%	7/17/2023 12:00	1,106.715	595,116,896.5	–0.004085809
50%	1/18/2024 0:00	1,211.5	719,932,658	0.000973172
75%	7/30/2024 12:00	1,259.69	916,465,482	0.005651024
Max	2/7/2025 0:00	1,301.51	1,708,947,942	0.034443953
STD	–	83.93920303	225,858,192.6	0.009440264

Note: Descriptive statistics of VNINDEX daily closing price, trading volume, and returns during the backtesting period (Jan 2023 – Feb 2025).