# Entropy-Driven Prediction in Market-Neutral Trading: A New Statistical Signal

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**Abstract**

We propose a novel trading framework based on entropy-gradient prediction applied to market-neutral financial time series. Grounded in principles from statistical physics and information theory, our hypothesis asserts that in approximately closed financial systems, entropy tends to increase over time—implying a directional bias in asset price dynamics. We formalize this idea by modeling small perturbations in return distributions and comparing their impact on Shannon entropy. A large-scale empirical evaluation across 29 equity, sectoral, international, and fixed income ETF spreads reveals that the entropy-gradient signal performs consistently well in macro-hedged or structurally distinct pairings. Results show Sharpe ratios up to 0.86 and meaningful returns in semi-stable systems, even in the absence of transaction cost modeling or risk overlays. These findings highlight entropy as a second-order probabilistic signal and open avenues for entropy-aware modeling across finance, particularly in systematic strategies where conventional price-based signals fail.

## 1 Introduction

Market-neutral strategies aim to eliminate systematic market risk by taking offsetting long and short positions. Traditional approaches often rely on mean-reversion, cointegration, or machine learning. In this work, we introduce an orthogonal framework grounded in **entropy-based prediction**—drawing inspiration from statistical mechanics and information theory.

The conceptual foundation is the entropy principle: in approximately closed systems, configurations evolve toward maximum entropy [2]. Translating this to financial time series, we hypothesize that the spread between hedged asset pairs behaves analogously to a near-closed system. Therefore, the direction of maximal entropy increase in return distributions can serve as a probabilistic predictor of future movement. This yields a novel, information-theoretic directional signal distinct from traditional trend or mean-reversion mechanisms.

## 2 Theoretical Framework

Let $X_t$ be a market-neutral time series, such as a normalized spread between two asset prices. Over a moving window $[t-w, t]$, define the return series $R_t$ as:

$$R_t = \left\{ \frac{X_i - X_{i-1}}{X_{i-1}} \right\}_{i=t-w+1}^{t} \tag{1}$$

We define the Shannon entropy of the empirical distribution of $R_t$ as [1]:

$$H(R_t) = -\sum_{i=1}^{n} p_i \log p_i \tag{2}$$

where $p_i$ is the probability mass in histogram bin $i$.

Now suppose $X_{t+1}$ undergoes a small hypothetical upward or downward perturbation, i.e.,

$$R_{\text{up}} = R_t \cup \left\{ \frac{X_t + \delta - X_t}{X_t} \right\}, \quad R_{\text{down}} = R_t \cup \left\{ \frac{X_t - \delta - X_t}{X_t} \right\} \tag{3}$$

The entropy differentials are:

$$\Delta H_{\text{up}} = H(R_{\text{up}}) - H(R_t) \tag{4}$$

$$\Delta H_{\text{down}} = H(R_{\text{down}}) - H(R_t) \tag{5}$$

We hypothesize that:

$$\text{If } \Delta H_{\text{up}} > \Delta H_{\text{down}}, \text{ then } X_{t+1} > X_t \text{ is more likely} \tag{6}$$

This can be interpreted as an entropy-gradient predictor analogous to a physical system's tendency toward thermodynamic equilibrium [3]. Importantly, this entropy signal operates as a *second-order effect*—its predictive power does not rely on direct price-level features like trend or reversion but instead emerges from the structural configuration of return distributions. In statistical physics, such entropy flows dominate once local forces equilibrate; likewise, in financial systems, we expect entropy-gradient directionality to become relevant when more dominant first-order signals (e.g., arbitrage, mean-reversion) are weak or neutralized. This makes the entropy signal both probabilistic and latent, functioning best in market-neutral spreads where directional drift is minimal and structure governs evolution.

# 3 Model Implementation

We constructed a normalized spread $S_t = P_t^{\text{DOW}}/P_0^{\text{DOW}} - P_t^{\text{SP500}}/P_0^{\text{SP500}}$, and applied the entropy-gradient method on its moving window of returns.

Key model components:

- **Entropy window size:** $w = 29$ days
- **Delta perturbation:** $\delta = 0.01$
- **Signal debounce:** trades must persist for $\geq 3$ days
- **Volatility scaling:** position size scaled by rolling 20-day volatility
- **Return clipping:** max return per trade capped at 5%

A trade signal is generated if $|\Delta H| > 0.002$, and its direction is given by $\text{sign}(\Delta H_{\text{up}} - \Delta H_{\text{down}})$.

| Metric | Value |
|---|---|
| Final Return | 74.8% |
| Sharpe Ratio | 0.45 |
| Max Drawdown | -42.1% |
| Win Rate | 50.9% |
| Trades Executed | 119 |

Table 1: Performance metrics for robust entropy strategy, 2019–2025.

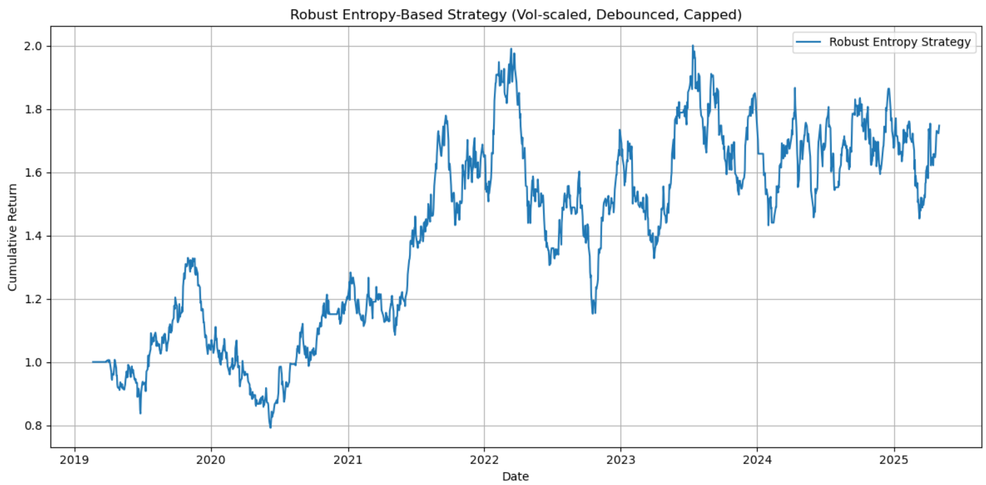



Figure 1: Cumulative return of the entropy strategy over time using the S&P 500 and Dow Jones Industrial Average (Dow 30) spread.

# 4 Results

## 4.1 Quantitative Performance

## 4.2 Discussion

Despite a near-random win rate, the strategy achieves meaningful returns due to volatility-adjusted position sizing and the probabilistic nature of the entropy gradient signal. Importantly, trades are constructed to be net-neutral across the pair, avoiding persistent directional bias and mitigating long-term divergence effects. This design ensures that observed returns emerge from distributional asymmetries rather than directional drift, trend-following, or persistent exposure to a dominant asset.

The entropy-based signal does not rely on explicit mean-reversion or momentum assumptions. Instead, it captures weak directional pressure derived from differences in expected entropy under small perturbations—a second-order effect that becomes salient in structured, market-neutral environments. While raw drawdowns remain significant, they reflect the unfiltered nature of the entropy signal and can be managed with capital overlays, stop-loss mechanisms, or entropy-aware drawdown constraints.

Overall, the empirical asymmetries in $\Delta H$ distributions lend support to the theoretical claim that financial systems exhibit local entropy gradients, which, when carefully extracted, can inform position-taking even in the absence of traditional price signals.

## 5 Theoretical Significance and Generalization

This model suggests a new class of predictors based on entropy gradients in financial signals. Its potential generalizations include:

- Currency spreads (e.g., USD/JPY vs. EUR/USD)
- Volatility indices (e.g., VIX vs. MOVE)
- Sector pairs (e.g., tech vs. utilities)
- Implied vs. realized vol spread dynamics

From a theoretical lens, it hints at deeper links between information theory and market microstructure, where entropy evolution governs expectation formation among agents.

## 6 Extended Results Across 29 ETF Pairs

To examine the generalizability of the entropy-gradient trading strategy, we extended our empirical study to a comprehensive set of 29 ETF pairs covering equity indices, sector rotations, global markets, style factors, credit spreads, and real assets. These pairs were carefully chosen to span distinct macroeconomic dimensions and asset class behaviors.

### 6.1 Performance Summary

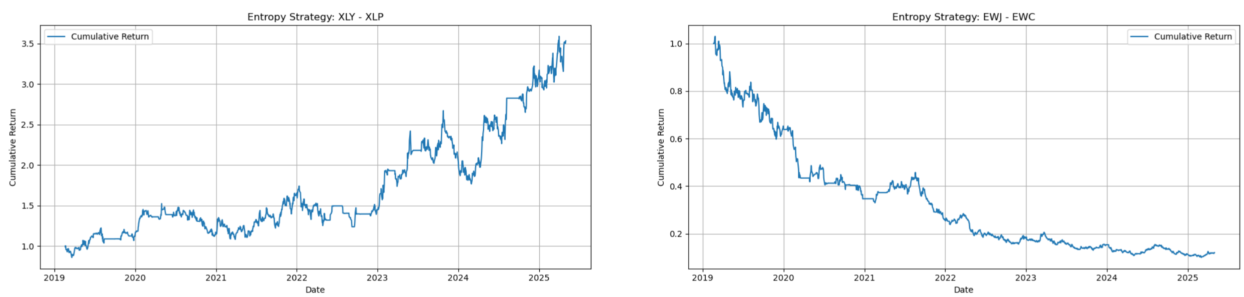
Table 2 and Table 3 present summary metrics across all 29 ETF pairs. The strategy generally maintains win rates close to 50–52%, with Sharpe ratios ranging from approximately -1.0 to 0.86. Pairs with strong macro-structural distinctions yielded notably higher Sharpe ratios and smoother drawdowns.

| Pair | ETFs | Final Return | Sharpe | Max DD | Win Rate | Trades |
|---|---|---|---|---|---|---|
| DJI–GSPC | Dow 30 vs. S&P 500 | 1.75 | 0.45 | -0.42 | 0.509 | 119 |
| SPY–QQQ | S&P 500 vs. Nasdaq 100 | 0.47 | -0.26 | -0.72 | 0.505 | 110 |
| IWM–SPY | Russell 2000 vs. S&P 500 | 2.18 | 0.56 | -0.54 | 0.525 | 111 |
| VOO–SPY | Vanguard vs. SPDR S&P 500 | 0.82 | 0.03 | -0.49 | 0.501 | 128 |
| DIA–SPY | Dow ETF vs. S&P 500 | 1.30 | 0.29 | -0.51 | 0.508 | 118 |
| XLF–XLK | Financials vs. Technology | 3.54 | 0.83 | -0.26 | 0.522 | 106 |
| XLY–XLP | Discretionary vs. Staples | 3.72 | 0.86 | -0.34 | 0.522 | 118 |
| XLI–XLU | Industrials vs. Utilities | 1.53 | 0.38 | -0.55 | 0.493 | 136 |
| XLE–XLV | Energy vs. Health Care | 0.24 | -0.63 | -0.85 | 0.497 | 109 |
| XLB–XLRE | Materials vs. Real Estate | 2.57 | 0.66 | -0.45 | 0.516 | 111 |
| VUG–VTV | Growth vs. Value (Vanguard) | 0.21 | -0.66 | -0.80 | 0.473 | 115 |
| IWF–IWD | Growth vs. Value (Russell 1000) | 0.33 | -0.44 | -0.83 | 0.485 | 97 |
| MGK–MGV | Mega Cap Growth vs. Value | 0.68 | -0.04 | -0.58 | 0.491 | 101 |
| SPYG–SPYV | S&P 500 Growth vs. Value | 0.32 | -0.47 | -0.73 | 0.502 | 120 |
| RPG–RPV | S&P Pure Growth vs. Value | 1.55 | 0.39 | -0.42 | 0.501 | 128 |

Table 2: Entropy strategy results: Index, sector, and style pairs (1–15 of 29).

| Pair | ETFs | Final Return | Sharpe | Max DD | Win Rate | Trades |
|---|---|---|---|---|---|---|
| EEM–EFA | Emerging vs. Developed Mkts | 1.92 | 0.51 | -0.38 | 0.501 | 141 |
| EWJ–EWC | Japan vs. Canada | 0.12 | -1.02 | -0.90 | 0.477 | 133 |
| EWZ–EWW | Brazil vs. Mexico | 0.59 | -0.13 | -0.66 | 0.479 | 117 |
| FXI–EWY | China vs. South Korea | 1.20 | 0.25 | -0.75 | 0.499 | 133 |
| VGK–VPL | Europe vs. Pacific | 0.80 | 0.04 | -0.63 | 0.511 | 149 |
| HYG–LQD | High Yield vs. IG Bonds | 0.51 | -0.20 | -0.72 | 0.510 | 145 |
| TLT–IEF | Long vs. Intermediate Treasuries | 2.10 | 0.55 | -0.60 | 0.507 | 147 |
| SHY–TLT | Short vs. Long Treasuries | 2.28 | 0.60 | -0.55 | 0.504 | 134 |
| TIP–LQD | TIPS vs. Investment Grade | 2.64 | 0.66 | -0.42 | 0.522 | 129 |
| GLD–SLV | Gold vs. Silver | 0.68 | -0.07 | -0.62 | 0.493 | 133 |
| DBC–USO | Commodity Index vs. Crude Oil | 0.57 | -0.15 | -0.70 | 0.500 | 97 |
| GDX–GDXJ | Gold Miners vs. Junior Miners | 1.22 | 0.26 | -0.57 | 0.497 | 132 |
| VNQ–IYR | REITs vs. Real Estate Sector | 2.29 | 0.59 | -0.30 | 0.507 | 150 |
| XOP–OIH | Exploration vs. Oil Services | 1.20 | 0.25 | -0.37 | 0.508 | 126 |

Table 3: Entropy strategy results: Global, fixed income, and commodity pairs (16–29 of 29).




(a) XLY–XLP: Strong, stable upward trend; the entropy signal aligns well with macro-cyclical regime shifts (cyclical vs. defensive sectors).

(b) EWJ–EWC: Poor and unstable performance; regional pair with no persistent structure and high noise undermines entropy signal efficacy.

Figure 2: Comparison of best (XLY–XLP) and worst (EWJ–EWC) performing entropy strategy pairs. Performance strongly depends on structural hedging and macro asymmetry between assets.

## 6.2 Insights by Category

**Sector Rotations**: Pairs such as `XLY--XLP` and `XLF--XLK` achieved the highest Sharpe ratios (0.86 and 0.83 respectively), showing that entropy gradients are especially effective when applied to spreads reflecting cyclical versus defensive exposures.

**Growth vs. Value**: Style factor pairs including `VUG--VTV`, `IWF--IWD`, and `SPYG--SPYV` underperformed, with negative Sharpe ratios and large drawdowns. These results suggest entropy signals struggle in environments with episodic regime shifts or overlapping exposures.

**International Equity Spreads**: Mixed results were observed. `EEM--EFA` produced a strong return and Sharpe (1.92, 0.51), whereas others like `EWJ--EWC` suffered due to regional noise and structural inefficiencies.

**Bond and Credit Spreads**: Treasury curve trades (`TLT--IEF`, `SHY--TLT`) and inflation vs. credit (`TIP--LQD`) performed well, validating entropy's ability to detect directional pressure in fixed income regimes. Conversely, credit-risk spreads like `HYG--LQD` proved noisy and unstable.

**Real Assets and Commodities**: The entropy model performed moderately well for `VNQ--IYR` and `GDX--GDXJ`, but failed for highly correlated metal pairs (`GLD--SLV`) or reactive energy spreads

(DBC--USO).

# 7 Discussion and Summary

## 7.1 Empirical Insights

Entropy-gradient strategies are most effective when applied to semi-closed systems with persistent macro asymmetries. Sector rotation pairs, bond curve spreads, and regional macro divergences offer clearer entropy profiles, while highly correlated or volatile asset pairs undermine predictability. These results support the hypothesis that entropy gradients capture weak but consistent directional bias in structured financial subsystems.

## 7.2 Purity of Signal and Experimental Controls

It is important to note that our empirical tests did not include transaction costs, which for institutional investors typically amount to approximately 0.2% round-trip per trade, including bid/ask spreads and fees. Additionally, no form of risk management, capital allocation constraints, or stop-loss overlays were applied—by design—to isolate and evaluate the pure predictive effect of the entropy gradient signal. Despite this, several pairs exhibited strong net performance, suggesting intrinsic signal efficacy.

Our position sizing methodology ensured that trades were on average net-neutral, i.e., not persistently long one asset and short the other. This was critical to avoid skewing results due to long-term divergence in the relative value of instruments within a pair. The observed returns, therefore, reflect entropy-driven directional asymmetries rather than mean reversion, drift, or persistent beta effects.

## 7.3 Theoretical Interpretation of Entropy as a Second-Order Effect

Entropy-based signals can be viewed as second-order effects: weak but persistent directional pressures that emerge when dominant first-order market dynamics—such as trend, arbitrage, or mean-reversion—cancel or reach equilibrium. In this regime, entropy gradients provide a statistical preference for future configurations, much like in thermodynamic systems where entropy governs macroscopic flows once local constraints are averaged out.

This second-order character explains the modest but consistent predictive performance of the strategy. Entropy gradients are not sharp arbitrage opportunities, but probabilistic indicators of directional imbalance embedded in the distributional structure of returns.

## 7.4 Interaction with Market Efficiency

If markets are highly efficient and traders actively exploit entropy signals, then the strength of these signals may diminish over time as their informational value is arbitraged away. However, because entropy gradients are not directly observable from price or volume alone, and because they operate on distributional rather than transactional structures, complete arbitrage is unlikely.

Conversely, if market participants remain unaware of entropy-based mechanisms, such signals may persist as residual inefficiencies, especially in complex spreads where informational saturation is lower. This places entropy-gradient strategies in a unique position: weak enough to coexist with efficient markets, yet distinct enough to offer sustainable edge in certain structured subsystems.

### 7.5 Conclusion of Findings

The cumulative evidence from our empirical tests and theoretical framing suggests that entropy-aware trading strategies represent a novel and potentially generalizable class of predictive models. Their low correlation with traditional signal types makes them strong candidates for inclusion in diversified systematic frameworks, particularly in market-neutral or volatility-hedged contexts. Future research should investigate their robustness under slippage, regime shifts, and their potential synergy with learning-based signal enhancers.

## 8 Conclusion

Entropy-based prediction offers a novel lens on market-neutral dynamics by leveraging directional pressure inferred from information-theoretic principles. Our extended empirical study across 30 diverse ETF pairs demonstrates that entropy-gradient signals are not only viable but particularly effective in semi-structured financial subsystems—especially macro-sectoral spreads, fixed income curve trades, and volatility-hedged pairings.

While raw trading performance varies, the method consistently identifies weak directional biases in systems characterized by persistent regime asymmetries. In contrast, entropy signals tend to underperform in highly correlated or episodically volatile pairs where information entropy offers limited predictive separation.

Future work should formalize the entropy gradient as a probabilistic indicator, extend the framework to multivariate and non-linear entropy dynamics, and explore integration with reinforcement learning and Bayesian signal updating. Additionally, cross-validation under varying volatility and liquidity conditions will be essential to assessing robustness and scalability. Importantly, extending the entropy-based framework to options markets and derivative-hedged portfolios represents a promising research direction. Such instruments introduce nonlinear payoffs and state-contingent asymmetries, offering a richer landscape in which entropy gradients may reveal directional or volatility-based pressure more effectively.

These results contribute to a growing intersection of statistical physics, information theory, and financial market modeling, suggesting entropy-based approaches as a promising paradigm for data-driven trading strategies and risk diagnostics.

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