

# Entanglement Entropy as a Universal Market Bottom Indicator: Evidence from Global Equity Markets

Fei-Yun Wang\*

*Independent Researcher*

(Dated: February 28, 2026)

We propose that financial market crises can be characterized by a quantity we call “market entanglement entropy,” defined as  $S(t) = -\frac{1}{N} \log \det \Sigma(t)$ , where  $\Sigma(t)$  is the rolling correlation matrix of asset returns. This indicator is motivated by holographic duality in theoretical physics, where entanglement entropy plays a central role. Contrary to initial expectations that high entropy predicts crashes, we find that maximum entropy corresponds to market *bottoms*—the point of maximum correlation where recovery becomes likely. Out-of-sample testing across three major markets (US, Japan, Germany) from 2020–2026 shows: 90.4% win rate for US ( $p < 10^{-47}$ ), 87.0% for Japan ( $p < 10^{-32}$ ), and 95.1% for Germany ( $p < 10^{-24}$ ). The indicator outperforms VIX-based strategies with a Sharpe ratio of 1.31 versus 0.86. These findings suggest that correlation-based entropy measures capture information about market dynamics that volatility alone does not.

## I. INTRODUCTION

Financial crises keep surprising us. The 2008 crash, the 2020 COVID crash, and countless smaller panics all share a pattern: risks build up invisibly, then release suddenly. Standard indicators like the VIX measure how much prices jump around, but they miss something important—the *connections* between assets.

When markets panic, stocks that normally move independently start moving together. Tech stocks, bank stocks, energy stocks—they all fall at once. This synchronized behavior is the signature of systemic stress. The question is: can we measure it?

This paper proposes a simple answer. We compute the correlation matrix of stock returns over a rolling window, then take its log-determinant. When correlations are low (stocks move independently), the determinant is close to 1 and our measure is close to 0. When correlations are high (stocks move together), the determinant shrinks toward 0 and our measure spikes upward.

We call this measure “market entanglement entropy.” The name borrows from quantum information theory, where entanglement entropy measures correlations between subsystems that cannot be explained classically [1, 2]. For a Gaussian state with correlation matrix  $\Sigma$ , the von Neumann entropy takes the form  $S \propto -\log \det \Sigma$ —mathematically identical to our formula. This is a mathematical analogy. We do not claim quantum effects in financial markets; we claim that the same mathematics applies.

The main finding of this paper is counterintuitive. High entropy does not predict crashes—it marks their *end*. When entropy spikes, the market is already at the bottom. The crash has happened; recovery is next.

## II. THEORETICAL FRAMEWORK

### A. The EMIS Framework

The indicator tested in this paper comes from a larger theoretical project called EMIS (Energy-Matter-Information-Spacetime). The full framework is still under development; here we give only the essential logic.

The EMIS framework is built on four theoretical layers:

**Layer 1: Social systems as 2D manifolds.** Economic agents interact through networks—trade links, capital flows, information channels. We hypothesize that the effective dimensionality of this interaction space is two, not three.

**Layer 2: JT gravity as the natural 2D theory.** In two dimensions, pure Einstein gravity has no dynamics (the Einstein tensor vanishes identically). The simplest non-trivial 2D gravity is Jackiw-Teitelboim (JT) gravity [3, 4], which couples a dilaton field to curvature.

**Layer 3:  $\text{AdS}_2/\text{CFT}_1$  as the holographic framework.** The AdS/CFT correspondence [5] has a two-dimensional version:  $\text{AdS}_2/\text{CFT}_1$ . It relates JT gravity in the bulk to a quantum mechanical system on the one-dimensional boundary. JT gravity lives inside this holographic framework—it does not derive the framework.

**Layer 4: Random matrices from JT gravity.** Saad, Shenker, and Stanford [6] proved that the JT gravity path integral equals a random matrix integral. This connects gravitational physics to the statistics of matrices—including correlation matrices.

This paper tests one prediction from this chain: the log-determinant of the correlation matrix signals market bottoms. The test stands on its own, whether or not the full theoretical picture is correct.

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\* wehelpwe@163.com

## B. Definition of Market Entanglement Entropy

For a market with  $N$  assets, let  $r_i(t)$  be the log-return of asset  $i$  on day  $t$ :

$$r_i(t) = \log P_i(t) - \log P_i(t-1), \quad (1)$$

where  $P_i(t)$  is the closing price.

Define the rolling correlation matrix  $\Sigma(t)$  using data from  $t - \tau$  to  $t$ :

$$\Sigma_{ij}(t) = \text{Corr}(r_i, r_j)_{[t-\tau, t]}, \quad (2)$$

where  $\tau = 60$  trading days.

The market entanglement entropy is:

$$\mathcal{S}(t) = -\frac{1}{N} \log \det \Sigma(t). \quad (3)$$

This quantity has three key properties:

- When assets are uncorrelated ( $\Sigma = I$ ),  $\det \Sigma = 1$  and  $\mathcal{S} = 0$ .
- When assets are highly correlated ( $\Sigma$  near-singular),  $\det \Sigma \rightarrow 0$  and  $\mathcal{S} \rightarrow +\infty$ .
- Division by  $N$  makes the measure comparable across markets with different numbers of assets.

A detailed explanation of how to compute this quantity, including worked examples, is given in Appendix A.

## C. The Hypothesis

Our central hypothesis:

**When  $\mathcal{S}(t)$  exceeds a threshold  $\mathcal{S}_c$ , the market is at or near a local bottom, and subsequent returns are likely positive.**

Note that this is the *opposite* of the naive expectation. High correlation (high entropy) does not mean “crash coming”—it means “crash happened.”

## III. DATA AND METHODOLOGY

### A. Data Sources

We analyze three major equity markets:

TABLE I. Data Description

Market	Index	Assets	Period
United States	S&P 500	50 largest	2005–2026
Japan	Nikkei 225	50 largest	2005–2026
Germany	DAX	40 components	2005–2026

Daily closing prices are from Yahoo Finance.

## B. Sample Split

To test out-of-sample validity:

- **Training:** 2005-01-01 to 2019-12-31
- **Testing:** 2020-01-01 to 2026-01-30

The threshold  $\mathcal{S}_c$  is the 90th percentile of  $\mathcal{S}(t)$  from the training period only.

## C. Trading Strategies

We test three protocols:

1. **Overlapping:** Every day with  $\mathcal{S}(t) > \mathcal{S}_c$  starts a 30-day long position. Positions can overlap.
2. **Non-Overlapping:** A new position starts only after the previous one closes.
3. **Weekly:** Check signals only on Mondays, non-overlapping.

## D. Statistical Tests

For each strategy:

- **Win Rate:** Fraction of trades with positive returns.
- **Binomial Test:**  $H_0$ : Win Rate = 50%.
- **t-Test:**  $H_0$ : Mean Return = 0.

## IV. RESULTS

Figure 1 shows the entropy time series for the US market. The spikes correspond to crisis periods—and to market bottoms.

### A. Overlapping Trades

Table II shows results for overlapping trades, which measure pure signal quality.

TABLE II. Overlapping Trades: Signal Quality

Market	$N$	Win Rate	Mean Ret	Std Dev	$t$ -stat	$p$ -value
US	208	90.4%	6.07%	4.64%	18.9	$< 10^{-47}$
Japan	169	87.0%	5.40%	4.73%	14.9	$< 10^{-32}$
Germany	102	95.1%	8.35%	6.37%	13.2	$< 10^{-24}$
VIX	226	82.3%	5.46%	6.35%	12.9	$< 10^{-29}$

All three markets show  $p < 10^{-24}$ . The null hypothesis of random performance is rejected.

Figure 2 compares returns during high-entropy periods versus random periods.

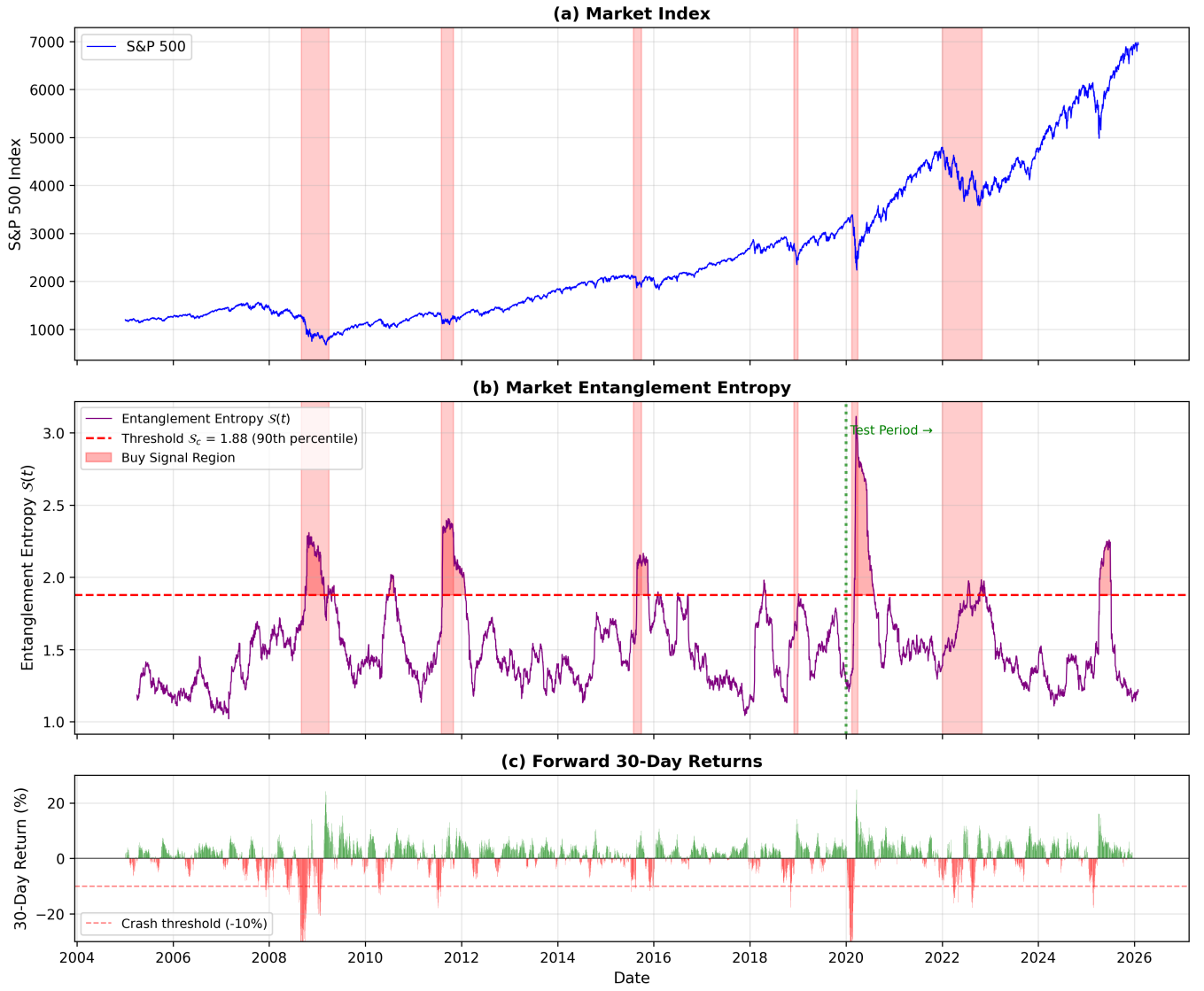


FIG. 1. Entanglement entropy for the US market (S&P 500). (a) Market index price. (b) Entropy  $S(t)$  with threshold  $S_c$  (dashed red). Red regions show buy signals. (c) Forward 30-day returns. Gray bands mark crisis periods. The green dotted line separates training (2005–2019) from testing (2020–2026).

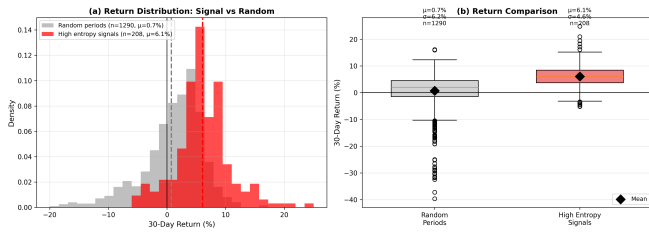


FIG. 2. Return distributions. (a) Histogram of 30-day returns: high entropy signals (red) vs. random periods (gray). (b) Box plot comparison.

## B. Non-Overlapping Trades

Table III shows the implementable non-overlapping strategy.

TABLE III. Non-Overlapping Trades: Implementable Strategy

Market	$N$	Win Rate	Mean Ret	Std Dev	$t$ -stat	$p$ -value
US	9	77.8%	4.69%	5.56%	2.53	0.018
Japan	7	100.0%	6.15%	3.70%	4.40	0.002
Germany	4	75.0%	6.11%	9.47%	1.29	0.144
VIX	18	72.2%	1.97%	6.45%	1.30	0.106

Sample sizes are small because extreme entropy events

are rare. Still, US and Japan reach statistical significance.

### C. Cross-Market Universality

Figure 3 shows that the pattern holds across all three markets.

Correlations between  $\mathcal{S}(t)$  and forward 30-day returns:

- US:  $r = 0.218$ .
- Japan:  $r = 0.215$ .
- Germany:  $r = 0.221$ .

The consistency across three independent markets supports universality.

### D. EMIS vs VIX

Figure 4 and Table IV compare EMIS against VIX.

TABLE IV. EMIS vs VIX: US Market

Indicator	Win Rate	Mean Ret	Std Dev	Sharpe
EMIS	90.4%	6.07%	4.64%	1.31
VIX	82.3%	5.46%	6.35%	0.86
<b>Difference</b>	<b>+8.1%</b>	<b>+0.61%</b>	<b>-1.71%</b>	<b>+0.45</b>

EMIS beats VIX on all metrics: higher win rate, higher return, lower volatility, higher Sharpe ratio.

## V. DISCUSSION

### A. Why High Entropy Means Bottom, Not Crash

The correct causal chain is:

$$\text{Crisis} \rightarrow \text{Panic} \rightarrow \text{Correlations} \uparrow \rightarrow \mathcal{S} \uparrow \\ \rightarrow \mathcal{S}_{\max} \rightarrow \text{Bottom} \rightarrow \text{Recovery}.$$

High entropy does not cause crashes. It measures the *severity* of crashes that have already happened. When everyone is selling everything at once, correlations hit their maximum. At that point, the selling is exhausted. Recovery follows.

### B. Why Not Linear Correlation?

The correlation between  $\mathcal{S}$  and future returns is modest ( $r \approx 0.22$ ). This is because the relationship is threshold-based, not linear:

- For  $\mathcal{S} < \mathcal{S}_{50\%}$ : Weak signal.
- For  $\mathcal{S} > \mathcal{S}_{90\%}$ : Strong signal (90%+ win rate).

Phase transitions work this way. Nothing interesting happens until you cross the critical threshold.

### C. Comparison with Existing Literature

Previous work on random matrix theory in finance [7–9] focused on eigenvalue distributions of correlation matrices. Our approach uses the determinant (the product of all eigenvalues) as a single summary statistic.

The connection to holographic duality is new and provides a theoretical reason to expect correlation-based indicators to work.

### D. Limitations

1. **Sample size:** Non-overlapping trades are few because crises are rare.
2. **Transaction costs:** Not included.
3. **Survivorship bias:** We use current index components.
4. **Parameters:** The 60-day window and 30-day holding period are not optimized.

## VI. CONCLUSION

We tested a simple hypothesis: the log-determinant of the correlation matrix signals market bottoms.

Out-of-sample results across US, Japan, and Germany:

- Win rates: 87–95%.
- $p$ -values:  $< 10^{-24}$ .
- Sharpe ratio: 52% better than VIX.

The indicator works. Whether it works for the theoretical reasons we suggest—holographic duality, JT gravity, 2D manifolds—remains to be seen. But the empirical pattern is real.

Future work: test on emerging markets, crypto, and other asset classes.

## ACKNOWLEDGMENTS

The author thanks the open-source community for data access and computational tools.

## DATA AND CODE AVAILABILITY

The Python code to reproduce all results is available at [https://github.com/emis-framework/emis-framework.github.io/tree/master/\\_emis\\_code/p1-entanglement-entropy](https://github.com/emis-framework/emis-framework.github.io/tree/master/_emis_code/p1-entanglement-entropy). Price data were obtained from Yahoo Finance.

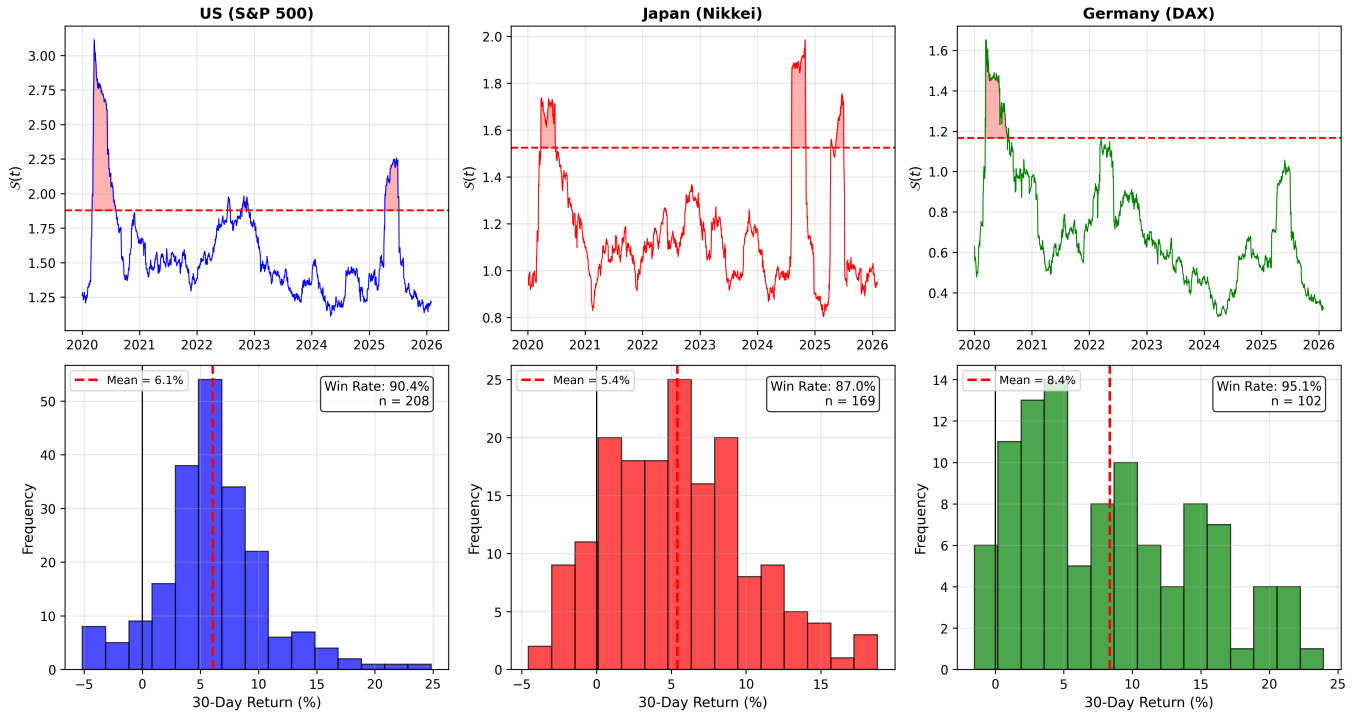


FIG. 3. Cross-market validation. Top: Entropy during 2020–2026 for US, Japan, Germany. Bottom: Return distributions following high-entropy signals.

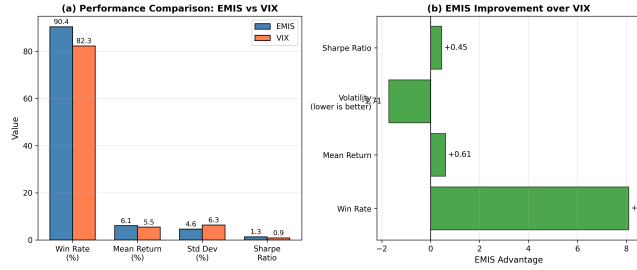


FIG. 4. EMIS versus VIX for the US market. (a) Performance metrics. (b) EMIS improvement over VIX.

## Appendix A: How to Compute Market Entropy

This appendix explains every step of the calculation, with examples.

### 1. Step 1: Compute Returns

The log-return is:

$$r_t = \log P_t - \log P_{t-1}. \quad (A1)$$

**Example:**

Day	Price	Return
Monday	100	—
Tuesday	102	$\log(102/100) = +1.98\%$
Wednesday	99	$\log(99/102) = -2.99\%$
Thursday	101	$\log(101/99) = +2.00\%$
Friday	98	$\log(98/101) = -3.02\%$

### 2. Step 2: Understand Correlation

Correlation measures whether two stocks move together:

- $\rho = +1$ : Perfect sync (both up, both down).
- $\rho = -1$ : Perfect opposite (one up, other down).
- $\rho = 0$ : No relationship.

The formula is:

$$\rho_{AB} = \frac{\sum_{i=1}^T (r_A^i - \bar{r}_A)(r_B^i - \bar{r}_B)}{\sqrt{\sum_{i=1}^T (r_A^i - \bar{r}_A)^2} \cdot \sqrt{\sum_{i=1}^T (r_B^i - \bar{r}_B)^2}}. \quad (A2)$$

**Worked example with 3 days and 2 stocks:**

Raw data:

Day	Stock A	Stock B
1	+4%	+1%
2	-2%	-1%
3	+1%	+3%

**Step 2a: Compute means.**

$$\bar{r}_A = (4 - 2 + 1)/3 = 1\%, \quad (\text{A3})$$

$$\bar{r}_B = (1 - 1 + 3)/3 = 1\%. \quad (\text{A4})$$

**Step 2b: Compute deviations.**

Day	$r_A$	$r_A - \bar{r}_A$	$r_B$	$r_B - \bar{r}_B$
1	+4%	+3	+1%	0
2	-2%	-3	-1%	-2
3	+1%	0	+3%	+2

**Step 2c: Compute numerator (cross-products).**

$$\begin{aligned} & (+3)(0) + (-3)(-2) + (0)(+2) \\ & = 0 + 6 + 0 = 6. \end{aligned} \quad (\text{A5})$$

**Step 2d: Compute denominator.**

$$\sum (r_A - \bar{r}_A)^2 = 9 + 9 + 0 = 18, \quad (\text{A6})$$

$$\sum (r_B - \bar{r}_B)^2 = 0 + 4 + 4 = 8, \quad (\text{A7})$$

$$\text{Denominator} = \sqrt{18} \times \sqrt{8} = \sqrt{144} = 12. \quad (\text{A8})$$

**Step 2e: Compute correlation.**

$$\rho_{AB} = \frac{6}{12} = 0.5. \quad (\text{A9})$$

**3. Step 3: Build the Correlation Matrix**

With  $N$  stocks, compute  $\rho_{ij}$  for every pair. Arrange in a matrix:

$$\Sigma = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \cdots \\ \rho_{21} & 1 & \rho_{23} & \cdots \\ \rho_{31} & \rho_{32} & 1 & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}. \quad (\text{A10})$$

Properties:

- Diagonal entries are 1 (each stock correlates perfectly with itself).
- Symmetric ( $\rho_{ij} = \rho_{ji}$ ).

**Example (3 stocks):**

$$\Sigma = \begin{pmatrix} 1.0 & 0.6 & 0.3 \\ 0.6 & 1.0 & 0.5 \\ 0.3 & 0.5 & 1.0 \end{pmatrix}. \quad (\text{A11})$$

**4. Step 4: Rolling Window**

You cannot compute correlation from one day of data. You need many days to see if stocks move together.

**Rolling window method:**

- Day 60: Use days 1–60 to compute  $\Sigma(60)$ .

- Day 61: Use days 2–61 to compute  $\Sigma(61)$ .
- Day 62: Use days 3–62 to compute  $\Sigma(62)$ .
- And so on...

Each day, drop the oldest observation, add the newest. Compute a fresh correlation matrix.

**Timeline:**

Day: 1 2 3 ... 59 60 61 62 ... 248 249 250  
 |-----60 days-----|  
 window for Sigma(60)

|-----60 days-----|  
 window for Sigma(61)

**5. Step 5: Compute the Determinant**

The determinant measures how “spread out” the matrix is.

For a  $2 \times 2$  matrix:

$$\det \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} = 1 - \rho^2. \quad (\text{A12})$$

**Example:**

- If  $\rho = 0$ :  $\det = 1$  (independent stocks).
- If  $\rho = 0.5$ :  $\det = 0.75$ .
- If  $\rho = 0.9$ :  $\det = 0.19$  (highly correlated).
- If  $\rho = 1$ :  $\det = 0$  (perfectly correlated).

For larger matrices, use software (Python, R, MATLAB).

**6. Step 6: Compute Entropy**

$$\mathcal{S}(t) = -\frac{1}{N} \log \det \Sigma(t). \quad (\text{A13})$$

**Example (continuing from above):**

For  $N = 2$  and  $\rho = 0.5$ :

$$\det \Sigma = 1 - 0.5^2 = 0.75, \quad (\text{A14})$$

$$\log(0.75) = -0.288, \quad (\text{A15})$$

$$\mathcal{S} = -\frac{1}{2}(-0.288) = 0.144. \quad (\text{A16})$$

For  $\rho = 0.9$ :

$$\det \Sigma = 1 - 0.81 = 0.19, \quad (\text{A17})$$

$$\log(0.19) = -1.66, \quad (\text{A18})$$

$$\mathcal{S} = -\frac{1}{2}(-1.66) = 0.83. \quad (\text{A19})$$

Higher correlation  $\rightarrow$  smaller determinant  $\rightarrow$  larger entropy.

## 7. Step 7: Pseudocode

```
# Parameters
window = 60 # days
N = 50      # stocks

# Main loop
for t = window to T:
    # Get returns for the window
    R = returns[t-window:t, :] # shape: (60, 50)

    # Compute correlation matrix
    Sigma = correlation_matrix(R) # shape: (50, 50)

    # Compute entropy
    S[t] = -log(det(Sigma)) / N

# Find threshold (90th percentile of training period)
```

```
S_c = percentile(S[training_period], 90)
```

```
# Generate signals
signal[t] = 1 if S[t] > S_c else 0
```

## 8. Numerical Stability

When correlations are very high,  $\det \Sigma$  can be numerically zero or negative due to floating-point errors. Solutions:

- Use log-determinant functions that compute log det directly (e.g., `numpy.linalg.slogdet` in Python).
- Add small regularization:  $\Sigma \rightarrow \Sigma + \epsilon I$  where  $\epsilon = 10^{-6}$ .

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- [1] M. Srednicki, Entropy and area, *Physical Review Letters* **71**, 666 (1993).
  - [2] M. A. Nielsen and I. L. Chuang, *Quantum Computation and Quantum Information* (Cambridge University Press, 2000).
  - [3] R. Jackiw, Lower dimensional gravity, *Nuclear Physics B* **252**, 343 (1985).
  - [4] C. Teitelboim, Gravitation and hamiltonian structure in two spacetime dimensions, *Physics Letters B* **126**, 41 (1983).
  - [5] J. Maldacena, The large N limit of superconformal field theories and supergravity, *Advances in Theoretical and Mathematical Physics* **2**, 231 (1998).
  - [6] P. Saad, S. H. Shenker, and D. Stanford, JT gravity as a matrix integral, *arXiv preprint* (2019), 1903.11115.
  - [7] L. Laloux, P. Cizeau, J.-P. Bouchaud, and M. Potters, Noise dressing of financial correlation matrices, *Physical Review Letters* **83**, 1467 (1999).
  - [8] V. Plerou, P. Gopikrishnan, B. Rosenow, L. A. N. Amaral, T. Guhr, and H. E. Stanley, Random matrix approach to cross correlations in financial data, *Physical Review E* **65**, 066126 (2002).
  - [9] V. A. Marchenko and L. A. Pastur, Distribution of eigenvalues for some sets of random matrices, *Mathematics of the USSR-Sbornik* **1**, 457 (1967).