Global and Local Balance in Financial Correlation Networks: A Unified Framework for Systemic Risk and Asset Selection

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June 18, 2026

Signed Networks and Structural Balance

What is a signed network?

- A network where relationships can be **positive** or **negative**
- Nodes: social, political, economic, financial actors (individuals, countries, firms, assets)
- Links:
  - $+$ friendship, alliance, trade partnership
  - $-$ rivalry, conflict, sanctions

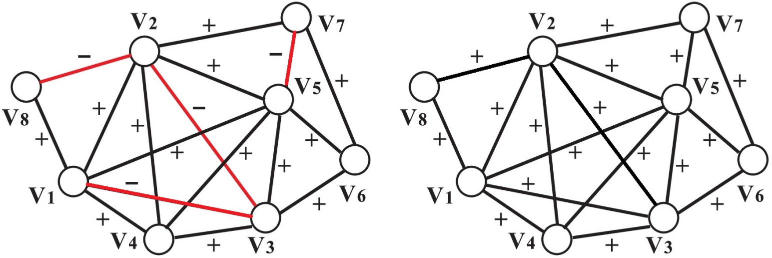
Formal definition:

- A graph where each link has a sign: $+$ or $-$

Examples

- International relations: alliances vs conflicts
- Trade networks: strong cooperation vs trade disputes
- Financial networks: positive vs negative asset correlations

Signed Networks and Structural Balance



(a) Signed graph

(b) Positive-edge graph

Signed Networks and Structural Balance

Structural balance (intuition)

- Focus on triangles (groups of three agents)
- A triangle is **balanced** if:
  - "The friend of my friend is my friend" $(+,+,+)$
  - "The enemy of my enemy is my friend" $(+,-,-)$
- Otherwise it is **unbalanced** (creates tension)

Economic intuition:

- Unbalanced structures are unstable and tend to evolve
- Networks move toward configurations with coherent alliances

Motivation: related evidence from the literature

Recent studies show that **signed**, **correlation-based**, and **hidden network structures** provide useful information for:

- portfolio analysis
- market fragility
- systemic risk

Signed graphs for portfolio analysis in risk management Get access >

Frank Harary, Meng-Hiot Lim, Donald C. Wunsch

IMA Journal of Management Mathematics, Volume 13, Issue 3, July 2002, Pages 201–210, https://doi.org/10.1093/imaman/13.3.201

Published: 01 July 2002

Article | Open access | Published: 09 June 2021

Loss of structural balance in stock markets

Eva Ferreira, Susan Orbe, Jone Ascorbebeitia, Brais Álvarez Pereira & Ernesto Estrada

Scientific Reports **11**, Article number: 12230 (2021) | Cite this article

RESEARCH ARTICLE | APPLIED PHYSICAL SCIENCES |

Hidden interactions in financial markets

Stavros K. Stavroglou, Athanasios A. Pantelous, H. Eugene Stanley, and Konstantin M. Zuev Authors Info & Affiliations

Contributed by H. Eugene Stanley, February 28, 2019 (sent for review February 7, 2019; reviewed by Grigoris Kalogeropoulos and Eugene Neduv)

May 13, 2019 | 116 (22) 10646-10651 | https://doi.org/10.1073/pnas.1819449116

Motivation

Motivating question

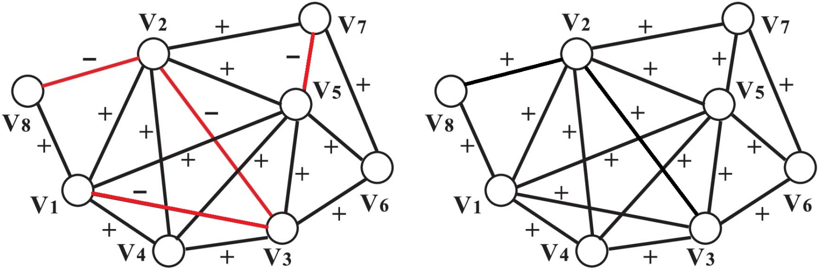
Can the structure of **signed financial networks** reveal which assets behave as **stabilizing components** during periods of **market stress**?

Logical Path

1. Construct a correlation-based network;
2. Introduce a diffusion process to define local and global balance;
3. Relate local balance to the condition number of the replication matrix;
4. Connect the condition number to spectral measures of systemic risk;
5. Interpret:
   - global balance as a systemic risk indicator,
   - local balance as the contribution of individual nodes to systemic risk;
6. Validate the framework using real financial datasets;
7. Develop a stock-picking strategy based on local balance during financial crises.

From diffusion model to balance indices

Let $x_i(t)$ be the information content of node i at discrete time $t \geq 0$.



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From diffusion model to balance indices

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$$x_i(t+1) = x_i(t) + \frac{1}{k+1} \sum_{j=1}^{N} A_{ij} \left[x_j(t) - x_j(t-1) \right].$$

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The **asymptotic state** is $\mathbf{x}_\infty = e^{\mathbf{A}} \mathbf{x}_0$. Suppose information spreads across the network, starting from node v only:
$\mathbf{x}_0 = [0, \ldots, 0, \underset{\substack{\downarrow \\ v}}{1}, 0, \ldots, 0]^T$, i.e. $x_{0i} = \delta_{iv}$. Then we have

$$\mathbf{x}_\infty = [e^{\mathbf{A}}]_v,$$

where $[e^{\mathbf{A}}]_v$ is the $v-$th column of the exponential matrix.

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$$\mathbf{x}_\infty = [e^{\mathbf{A}}]_v,$$

where $[e^{\mathbf{A}}]_v$ is the $v-$th column of the exponential matrix. The **amount of information that returns to the same node**, after the diffusion process has reached the steady state, is

$$\mathbf{x}_{\infty,v} = [e^{\mathbf{A}}]_{vv}.$$

Local Balance Index

To measure information retention at node v despite signed edges, define the *local balance* as

$$\kappa_v := \frac{[e^{\mathbf{A}}]_{vv}}{[e^{|\mathbf{A}|}]_{vv}}.$$

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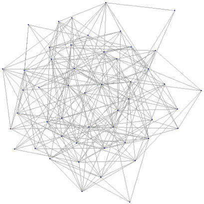
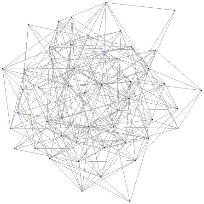
$$\boxed{\kappa_v := \frac{[e^{\mathbf{A}}]_{vv}}{[e^{|\mathbf{A}|}]_{vv}}.}$$

This ratio quantifies the amount of **information preserved locally** in the **non-conservative diffusion process** on the **signed graph** compared to the corresponding **unsigned graph**.

Diffusion on simulated network examples



Evolution on unbalanced network



Evolution on balanced network

Global Balance Index

The *global balance* index of the network is defined as

$$\kappa_G = \frac{\sum_{v=1}^{N} [e^{\mathbf{A}}]_{vv}}{\sum_{v=1}^{N} [e^{|\mathbf{A}|}]_{vv}} = \frac{\mathrm{tr}[e^{\mathbf{A}}]}{\mathrm{tr}[e^{|\mathbf{A}|}]} = \frac{\sum_{i=1}^{N} e^{\lambda_i}}{\sum_{i=1}^{N} e^{\overline{\lambda}_i}},$$

where λ_i and $\overline{\lambda}_i$ are eigenvalues of $\mathbf{A}$ and $|\mathbf{A}|$, respectively.

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where λ_i and $\overline{\lambda}_i$ are eigenvalues of $\mathbf{A}$ and $|\mathbf{A}|$, respectively.

Key property: A network is balanced if and only if $\kappa_G = 1$, or equivalently $\kappa_v = 1$ for all v.

From Structural Balance to System Conditioning

Core Relationship

$\boxed{\kappa_G \propto \mathrm{cond}(e^{\mathbf{A}})}$ where

κ_G : Global balance index

$\mathrm{cond}(e^{\mathbf{A}})$: Condition number of the matrix exponential

Perturbation Protocol

- Node-specific impulse: $\Delta \mathbf{x}_0 = \varepsilon \mathbf{e}_v$
- Scaled basis vector: $\varepsilon \in \mathbb{R},\ \{\mathbf{e}_v\} \in \mathbb{R}^n$

Propagation Response

$$\Delta \mathbf{x}_\infty = \varepsilon \underbrace{[e^{\mathbf{A}}]_v}_{\text{Network impulse response}}$$

From Structural Balance to System Conditioning

Core Relationship

$\boxed{\kappa_G \propto \mathrm{cond}(e^{\mathbf{A}})}$ where

κ_G : Global balance index

$\mathrm{cond}(e^{\mathbf{A}})$: Condition number of the matrix exponential

Theorem (Nodal Sensitivity Measure)

$$\frac{|\Delta \mathbf{x}_{\infty,v}|}{|\Delta \mathbf{x}_{0,v}|} = \underbrace{[e^{\mathbf{A}}]_{vv}}_{\textit{Autocorrelation amplification}}$$

From Structural Balance to System Conditioning

Core Relationship

$$\boxed{\kappa_G \propto \mathrm{cond}(e^{\mathbf{A}})} \quad \text{where}$$

κ_G : Global balance index

$\mathrm{cond}(e^{\mathbf{A}})$: Condition number of the matrix exponential

Key Interpretation

- Local balance $\kappa_v := \dfrac{[e^{\mathbf{A}}]_{vv}}{[e^{|\mathbf{A}|}]_{vv}}$
- Ratio of signed ($\mathbf{A}$) to unsigned ($|\mathbf{A}|$) network responses
- $\kappa_v < 1 \Rightarrow$ Signed networks suppress perturbations

From Structural Balance to System Conditioning

Perturbation Sensitivity Framework

- Core problem: $e^{-\mathbf{A}}\mathbf{x}_\infty = \mathbf{x}_0$
- Perturbation vector: $\mathbf{e} \in \mathbb{R}^n$
- Condition number quantifies solution stability

From Structural Balance to System Conditioning

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Matrix Exponential Conditioning

$$\mathscr{K}(e^{-\mathbf{A}}) = \underbrace{\|e^{-\mathbf{A}}\|_1}_{\text{Forward stability}} \cdot \underbrace{\|e^{\mathbf{A}}\|_1}_{\text{Backward stability}} = \left(\sum_{i=1}^{N} e^{-\lambda_i}\right) \cdot \left(\sum_{i=1}^{N} e^{\lambda_i}\right)$$

From Structural Balance to System Conditioning

Ratio of the Condition Numbers

$$\mathscr{R}(\mathbf{A}) = \frac{\overbrace{\mathscr{K}(e^{-\mathbf{A}})}^{\text{Signed}}}{\underbrace{\mathscr{K}(e^{-|\mathbf{A}|})}_{\text{Unsigned}}} = \frac{\kappa(G) \cdot \kappa(-G)}{\kappa(-|G|)}$$

- $\kappa(G)$: Global balance of G
- $\kappa(-G)$: Global balance of the sign-flipped graph
- $\kappa(-|G|)$: Global balance of the fully negative graph

From Structural Balance to System Conditioning

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Theorem (Necessary Condition)

$$G \textit{ balanced or antibalanced } \Rightarrow \mathscr{R}(\mathbf{A}) = 1$$

Correlation-based financial networks

Daily log-returns of N assets over T days are $X_{it} = \log \frac{P_{i,t+1}}{P_{i,t}}$ $\mathbf{X} \in \mathbb{R}^{N \times T}$. After standardization $\tilde{X}_{it} = \frac{X_{it} - \mu_i}{\sigma_i}$: $\mathbf{C} = \frac{1}{T}\tilde{\mathbf{X}}\tilde{\mathbf{X}}^T$ and a signed binary network $\mathbf{A}$ is obtained by thresholding the correlation matrix $\mathbf{C}$.

For large spectral gaps,

$$\mathscr{R}(\mathbf{A}) \approx \frac{1 + \frac{2}{N}\sum_{j=2}^{N} \cosh \Delta\lambda_{1j}}{1 + \frac{2}{N}\sum_{j=2}^{N} \cosh \Delta\overline{\lambda}_{1j}}.$$

Since $\lambda_1 \leq \overline{\lambda}_1$, with strict inequality iff the signed network is strictly unbalanced, we obtain:

Key insight

Strictly unbalanced financial networks tend to have $\mathscr{R}(\mathbf{A}) < 1$, suggesting lower sensitivity to perturbations and greater resilience to shocks.

Correlation-based financial networks

Structural balance shapes financial resilience

Unbalanced networks

Absorb shocks

Lower condition numbers imply greater numerical stability and better perturbation mitigation.

Balanced networks

Amplify shocks

Higher sensitivity to perturbations can translate into stronger instability under stress.

Key implication: the signed structure of correlations affects how financial shocks propagate through the system.

From Conditioning to Systemic Risk

Market Rank Indicators (MRI)

Two generalized condition number measures for systemic risk:

Arithmetic MRI

$$\mathrm{AMRI} = \frac{\lambda_1}{\left(\frac{1}{k} \sum_{i=n-k+1}^{n} \lambda_i^p \right)^{1/p}}$$

Geometric MRI

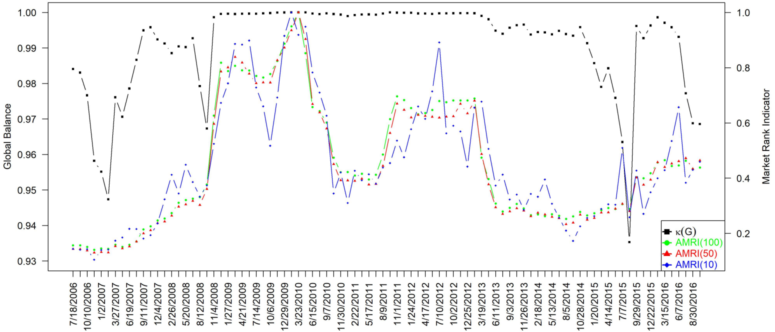
$$\mathrm{GMRI} = \frac{\lambda_1}{\left(\prod_{i=n-k+1}^{n} \lambda_i \right)^{1/k}}$$

where $1 \leq k \leq N$ and $p \in \mathbb{N}$. Both indicators

- generalize condition number $\frac{\lambda_1}{\lambda_n}$ when $k = 1$;
- are already validated as effective systemic risk measures.

Numerical Analysis: correlation with MRI

Daily returns of a subset of 385 assets from the S&P dataset from January 4, 2005 to March 18, 2020 ($T = 4109$ days).



Time evolution of the global balance (black square dot line) and of the market rank indicator for $p = 3$ and $k = 10$ (blue kite dot line), $k = 50$ (red triangle dot line) and $k = 100$ (green circle dot line).

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Numerical Analysis: correlation with MRI

	Correlations between Global balance and MRI			
	2005-2016		**2016-2020**	
k	Pearson	Spearman	Pearson	Spearman
10	0.51043890	0.75268360	0.65198390	0.81116310
50	0.53938464	0.81110470	0.65998890	0.90441180
100	0.55415830	0.82765060	0.65877970	0.89204550
385	0.87786900	0.89459170	0.88014410	0.98061500

Correlations between Global balance and MRI in the two intervals 2005-2016 and 2016-2020, for different values of k in the definition of the MRI.

Detecting Systemic Risk Through Network Balance

- **Event Identification**
  - Systemic event when:
    $$\frac{1}{N}\sum X_{it} < \tau \text{ for } \Delta T = 20 \text{ days}$$
  - Thresholds tested:
    $\tau = -0.01$ and
    $\tau = -0.005$

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- **Distribution Analysis**
  - Binned κ_G values:
    - Equal width (5 bins)
    - Risk-focused partitioning
  - Computed conditional distributions:

    $$P(\langle X_{it} \rangle | \kappa_G \in B_k)$$

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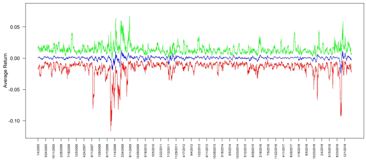
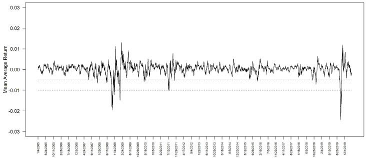
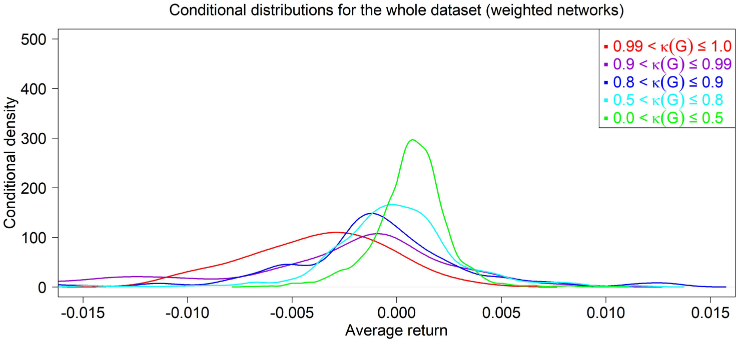




Average returns
Gaussian kernel smoothing applied

Detecting Systemic Risk Through Network Balance

Conditional return densities across κ_G bins for S&P dataset (385 assets) from Jan 4, 2005 to Mar 18, 2020.



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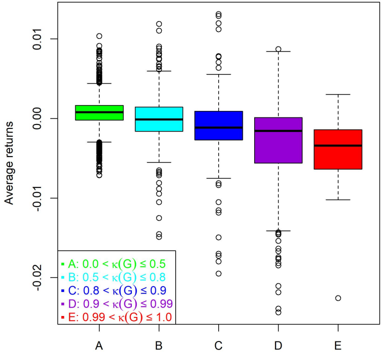

Detecting Systemic Risk Through Network Balance

Mean of the average returns in the different balance intervals.

Mean of the average returns				
$0 < \kappa_G \leq 0.2$	$0.2 < \kappa_G \leq 0.4$	$0.4 < \kappa_G \leq 0.6$	$0.6 < \kappa_G \leq 0.8$	$0.8 < \kappa_G \leq 1.0$
0.0007890292	0.0002017107	−0.00008924373	−0.00009901411	−0.002686201
$0 < \kappa_G \leq 0.5$	$0.5 < \kappa_G \leq 0.8$	$0.8 < \kappa_G \leq 0.9$	$0.9 < \kappa_G \leq 0.99$	$0.99 < \kappa_G \leq 1.0$
0.0006679086	−0.00009905363	−0.001337312	−0.003448823	−0.004218843

Detecting Systemic Risk Through Network Balance

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Key Findings

1. $\uparrow \kappa_G \Rightarrow \downarrow$ mean returns
2. $\uparrow \kappa_G \Rightarrow \uparrow$ volatility
3. $\uparrow \kappa_G \Rightarrow \uparrow$ VaR

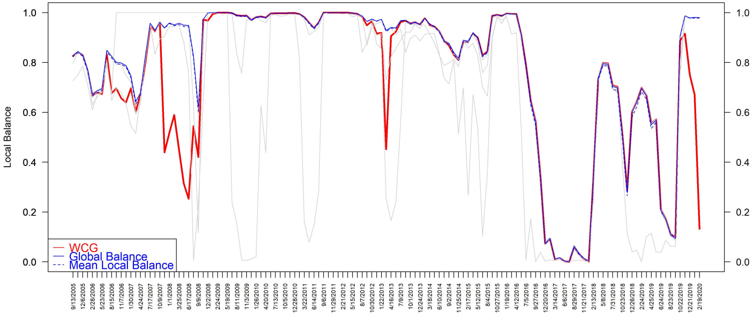
Different financial indices

	Global Balance - AMR	Global Balance - SR
DAX	-0.249 (-0.261)	-0.269 (-0.277)
ESX	-0.193 (-0.250)	-0.233 (-0.286)
FTSE	-0.277 (-0.320)	-0.245 (-0.310)
NIKKEI	-0.421 (-0.456)	-0.476 (-0.461)

Pearson (Spearman in brackets) correlations between global balance and both average market return (AMR) and Sharpe ratio (SR).

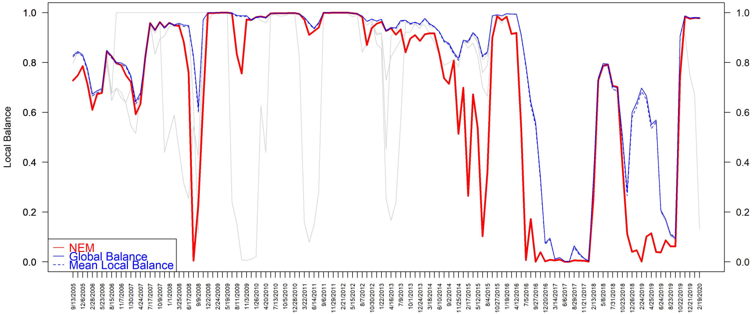
Final assumption: As κ_G increases, average returns and Sharpe ratios *decrease*. Global balance acts as a systemic risk indicator.

Key Insights from Local Balances



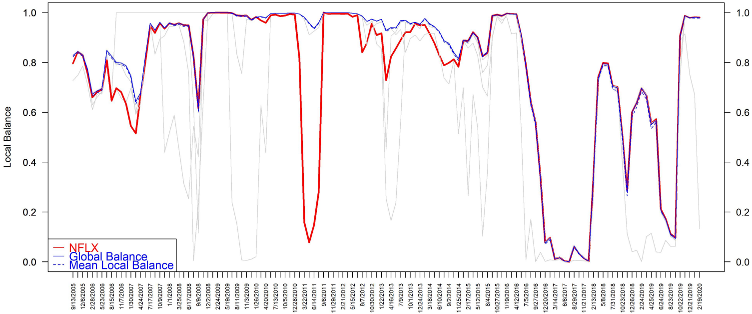
Global balance (solid blue line), mean local balance (dashed blue line) and local balance of WCG (red line) in the weighted network.

Key Insights from Local Balances



Global balance (solid blue line), mean local balance (dashed blue line) and local balance of NEM (red line) in the weighted network.

Key Insights from Local Balances



Global balance (solid blue line), mean local balance (dashed blue line) and local balance of NFLX (red line) in the weighted network.

Motivation for Asset Selection

During financial crises correlations increase, limiting standard diversification. In such circumstances:

- Most assets behave similarly; losses are severe and widespread
- Global balance κ_G of the signed network approaches its maximum value (close to 1)
- Standard diversification (mainly related to portfolio size) is unable to reduce risk or limit losses

Claim: Assets whose local balance significantly departs from the global balance can be identified as potential safe-haven assets that hedge losses and outperform the market during crises.

Stock Picking Strategy in Crisis Periods

Research Question

Can we develop a crisis-resilient stock picking strategy that exploits market synchronization ($\kappa_G \to 1$) through local balance deviations?

Proposed Strategy:

- **Step 1:** Detect critical periods
  - Strong synchronization
  - High global balance κ_G
- **Step 2:** Stock selection
  - Local balance $\neq \kappa_G$
  - Threshold-based filtering
- **Step 3:** Performance analysis
  - Return distribution
  - Sharpe ratio analysis
- **Step 4:** Validation
  - In-sample testing
  - Out-of-sample verification

Asset Selection Procedure

We select two thresholds τ_G and τ_L to simultaneously identify when:

1. Global balance is significantly high: $\kappa_G(t) \geq \tau_G$
2. Local balance deviates significantly: $\kappa_G(t) - \kappa_i(t) \geq \tau_L$

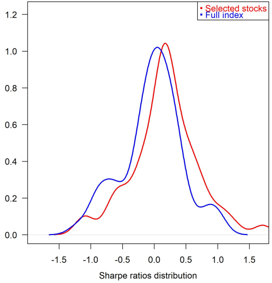
The set of **selected assets** is:

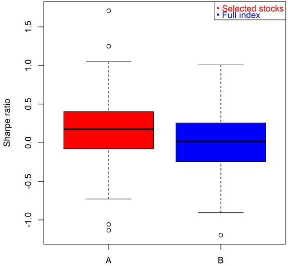
$$S_A = \left\{ i = 1, \ldots, N : \kappa_G(t) \geq \tau_G,\ \kappa_G(t) - \kappa_i(t) \geq \tau_L \right\}$$

Portfolio construction rule:

- When selection conditions hold, equally weighted portfolio of assets in S_A (improved $1/N$ portfolio)
- Otherwise: equally weighted portfolio of random selected assets (standard $1/N$ portfolio)

Sharpe ratio of selected stocks against remaining stocks





Sharpe ratios of selected stocks (red) vs. remainder (blue) for NIKKEI Index with $\tau_G = 0.90$, $\tau_L = 0.45$ (p-value Kolmogorov-Smirnov test: $= 0.02456$).
To ensure consistent comparison, we randomly sample from remaining stocks a number equal to $|S_A|$, repeated 10 000 times.

Distribution Moments

In-sample distribution moments for Sharpe ratios, NIKKEI ($\tau_G = 0.90$, $\tau_L = 0.45$).

Group	Mean	Variance	Skewness	Kurtosis
Selected stocks	0.170	0.285	0.067	3.696
Remaining stocks	-0.031	0.227	-0.213	2.992

Selected stocks are characterised by:

- Higher mean Sharpe ratio
- Fatter right tail, thinner left tail
- Positive skewness vs. negative skewness for the remainder

Selected stocks: Nikkei crisis macroperiods 2005-2010

Macroperiod / Crisis episode	Company	Sector / Industry
16 Feb 2005 – 02 Apr 2006	Bandai Namco Holdings Inc.	Consumer Discretionary / Leisure
Japanese equity market stress and Livedoor shock	Tokio Marine Holdings, Inc.	Financials / Insurance
21 Oct 2008 – 05 Mar 2010	Nitori Holdings Co., Ltd.	Consumer Discretionary / Specialty Retail
Global Financial Crisis and Great Recession	Osaka Gas Co., Ltd.	Utilities / Regulated Gas
	The Kansai Electric Power Company, Inc.	Utilities / Electric Utilities

Selected stocks: Nikkei crisis macroperiods 2010-2013

Macroperiod / Crisis episode	Company	Sector / Industry
18 May 2010 – 13 Apr 2013	Rakuten Group, Inc.	Consumer Discretionary / Internet Retail
Euro-area sovereign debt crisis, Great East Japan Earthquake and Fukushima	M3, Inc.	Healthcare / Health Information Services
	Tokyo Gas Co., Ltd.	Utilities / Regulated Gas
	Tokyo Electric Power Company Holdings, Inc.	Utilities / Electric Utilities
	Nitori Holdings Co., Ltd.	Consumer Discretionary / Specialty Retail
	Yakult Honsha Co., Ltd.	Consumer Staples / Packaged Foods
	Ajinomoto Co., Inc.	Consumer Staples / Packaged Foods
	CyberAgent, Inc.	Communication Services / Advertising Agencies

Selected stocks: Nikkei crisis macroperiods 2016-2025

Macroperiod / Crisis episode	**Company**	**Sector / Industry**
14 Apr 2016 – 18 Mar 2018	Nitori Holdings Co., Ltd.	Consumer Discretionary / Specialty Retail
Brexit, China slowdown and yen appreciation	Nichirei Corporation	Consumer Staples / Packaged Foods
18 Apr 2019 – 07 Sep 2020	Konami Group Corporation	Communication Services / Electronic Gaming & Multimedia
COVID-19 market crash and US–China trade-war stress	Yakult Honsha Co., Ltd.	Consumer Staples / Packaged Foods
30 Dec 2022 – 04 Jul 2023	Nitori Holdings Co., Ltd.	Consumer Discretionary / Specialty Retail
BoJ yield-curve-control adjustment and policy-normalization stress		
08 Mar 2024 – 06 Apr 2025	Nitori Holdings Co., Ltd.	Consumer Discretionary / Specialty Retail
Japanese policy normalization and yen carry-trade unwind		

Selected stocks

Across the seven crisis macroperiods, the proposed rule selects stocks displaying a clear **defensive pattern**.

- Crisis-period selections remain concentrated in **resilient sectors**: utilities, consumer staples, healthcare-related services, communication services, internet retail, and digital entertainment
- Examples:
  - 2008–2010: Nitori Holdings, Osaka Gas, Kansai Electric Power
  - 2010–2013: utilities, staples, healthcare-related services, internet retail, communication services
  - 2019–2020: Konami Group, Yakult Honsha
- Firms are typically characterized by:
  - **Inelastic demand** for basic goods and essential services
  - **Stable cash flows** from regulated or contract-based revenues
  - **Lower earnings volatility**
- Overall, the evidence supports a **safe-haven interpretation**: during stress, investors reallocate toward firms tied to basic consumption and essential services

In-sample distribution moments for Sharpe ratios of selected stocks and remaining dataset for DAX, ESX, FTSE and NIKKEI indices. The differences between the two means is always statistically significant:
DAX: p.value=0.02225; ESX: p.value=0.02548; FTSE: p.value=0.04978; NIKKEI: p.value=0.003627.

Index	Group	τ_G	τ_L	Mean	Variance	Skewness	Kurtosis
DAX	Selected	0.75	0.45	0.054	0.331	-0.233	4.704
	Remaining	0.75	0.45	0.022	0.164	0.159	3.870
ESX	Selected	0.75	0.45	0.031	0.366	-0.257	4.008
	Remaining	0.75	0.45	-0.047	0.163	-0.086	4.761
FTSE	Selected	0.90	0.60	-0.022	0.453	-0.206	2.539
	Remaining	0.90	0.60	-0.141	0.179	-0.753	2.468
NIKKEI	Selected	0.90	0.60	0.188	0.299	-0.004	3.673
	Remaining	0.90	0.60	0.054	0.107	0.758	3.643

Out-sample distribution moments for Sharpe ratios of selected stocks and remaining dataset for DAX, ESX, FTSE and NIKKEI indices. The differences between the two means is always statistically significant:
DAX: p.value=0.1786; ESX: p.value=0.08457; FTSE: p.value=0.001279; NIKKEI: p.value=0.06236.

Index	Group	τ_G	τ_L	Mean	Variance	Skewness	Kurtosis
DAX	Selected	0.70	0.40	0.412	0.358	0.791	1.818
	Remaining	0.75	0.45	0.096	0.051	0.177	1.132
ESX	Selected	0.80	0.50	0.0788	0.203	-0.841	4.601
	Remaining	0.80	0.50	0.032	0.129	-0.298	3.134
FTSE	Selected	0.90	0.45	0.208	0.230	0.004	3.335
	Remaining	0.90	0.45	0.018	0.061	-0.143	4.246
NIKKEI	Selected	0.95	0.45	0.160	0.233	-0.395	2.797
	Remaining	0.95	0.45	0.087	0.156	0.202	3.475

Policy Implications

- **Crisis detection**: When κ_G exceeds τ_G (e.g. 0.75–0.90), the market is in a high-systemic-risk regime.
- **Portfolio reallocation**: Concentrate on assets with $\kappa_G - \kappa_i \geq \tau_L$; these display resilience precisely when diversification is most needed.
- **Threshold guidance**:
  - τ_G: choose high (close to 1) for conservative crisis identification; lower values trigger more frequent reallocation;
  - τ_L: controls concentration level; larger values yield fewer but more extreme portfolio tilts.
- **Applications**: Portfolio management, Hedging strategies, Algorithmic trading

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Physica A: Statistical Mechanics and its Applications

Volume 674, 15 September 2025, 130698

Global balance and systemic risk in financial correlation networks

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Thank you for your attention.

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