Symmetry Breaking and Chimera States: A New Taxonomy of Amalgams in Complex Financial Networks

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Abstract

We investigate the collective dynamics of financial markets through the lens of phase transitions and synchronization in complex networks. Using a system of 29 global assets categorized into risk and safe-haven clusters, we apply the Hilbert Transform to extract instantaneous phases and compute the Kuramoto order parameter (R) alongside a novel Chimera Index (H). Our results reveal that systemic crises, such as the 2008 Subprime collapse and the 2020 pandemic, are characterized by a forced phase condensation where synchronization is driven by volatility ($\partial R/\partial \sigma > 0$), leading to a "Systemic Amalgam" state. Conversely, geopolitical shifts like the 2016 and 2024 U.S. elections trigger "Chimera States", marked by the coexistence of synchronized and desynchronized subpopulations. By mapping these transitions onto a Landau free-energy potential, we demonstrate that the Chimera state serves as a meta-stable precursor to symmetry breaking. This thermodynamic framework provides a robust early-warning signal for systemic risk, identifying structural fragility before global diversification collapses.

Keywords: Econophysics, Chimera states, Phase transitions, Hilbert transform, Systemic risk, Symmetry Breaking.

1 Introduction

The stability of global financial systems has been historically analyzed under the premise of the Efficient Market Hypothesis (EMH) [8] and through linear correlation metrics applied to Modern Portfolio Theory [15]. However, recent systemic crises — such as the 2008 Subprime collapse, the 2020 pandemic shock, and the geopolitical disruptions of the 2020s — have demonstrated that market interconnectivity is neither static nor linear [4, 14]. The core problem lies in the failure of traditional metrics to detect phase transitions: the moment when individual assets lose their autonomy and the system freezes into a herding behavior. Pearson correlation, while useful in normal regimes, proves insufficient for capturing the nonlinear nature of informational causality and the phase dynamics that precede systemic chaos [16].

The need for a new framework becomes evident as portfolio diversification fails precisely at the moments of greatest vulnerability. This investigation is justified by the urgency of developing Early Warning Signals that identify the market's topological fragility before its materialization into nominal losses. Unlike classical econometric models that often treat risk as an exogenous variable or a point shock [7], this research is grounded in Econophysics, treating financial assets

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as coupled oscillators in a complex network. The originality of this work lies in the proposition that systemic risk is not merely a synchronized drop in prices, but a fundamental rupture in the phase symmetry of the system. Although literature has explored synchronization in finance [6], our proposition is original in formalizing risk through the symmetry breaking of chimera states specifically mapped onto the Landau potential.

To address this problem, we adopt a methodology based on complex systems dynamics and information theory. First, we utilize the Hilbert Transform to extract the instantaneous phase, a consolidated technique in physics [9] with increasing applications in financial cycles [20]. Secondly, we apply Transfer Entropy (TE) to map the asymmetric information flow [23, 25]. The analytical core employs the Kuramoto Model to quantify synchrony [10, 19] and Landau Theory to describe the energy potential [12], allowing for the identification of Chimera States [1, 13] as precursors of instability.

The main theoretical innovation of this work lies in the proposition of a new taxonomy for high-synchrony states. We introduce the fundamental distinction between Structural Amalgam and Systemic Amalgam. The former is defined as a low-energy order regime, reflecting an organic integration. In contrast, the Systemic Amalgam is presented as a phase condensation forced by thermal stress (volatility). This differentiation, grounded in the derivative of synchrony with respect to volatility ($\partial R/\partial\sigma$), allows us to identify whether market cohesion is the result of a solid economic architecture or a coercive contagion mechanism.

The remainder of this article is organized as follows: Section 2 presents the theoretical foundation detailing the Kuramoto Model and Chimera phenomenology; Section 3 describes the signal processing methodology and the database; Section 4 introduces the Differential Proof and the new taxonomy; Section 5 discusses the empirical results across historical landmarks; and finally, Section 6 presents the conclusions and implications for macroprudential regulation.

2 Model

The proposed methodological approach integrates tools from signal theory, information theory, and statistical mechanics to characterize the network topology of the financial system. The process is divided into three sequential stages: phase extraction, causality mapping, and modeling of collective synchronization.

Synchronization analysis in financial systems has its roots in the application of correlation matrices subjected to filters from Random Matrix Theory (RMT) [11, 22]. This technique was fundamental to the advancement of econophysics by allowing the isolation of statistical noise from genuine informational components, revealing that the dependency structure of financial assets is not purely random but contains signatures of collective behavior.

Recent developments have expanded this view by integrating complex network theory [3, 29], which made it possible to map the market as highly dynamic influence graphs. In these networks, topology dictates the efficiency of shock propagation and the robustness of the system [4]. However, it is observed that traditional literature has focused mainly on static metrics [17] or correlations based on raw returns [14], which often conceals the underlying oscillatory nature of market cycles.

Our work advances beyond these approaches by adopting the dynamics of Kuramoto phase oscillators [2, 27]. This methodology allows for the unprecedented mapping of Chimera States [1, 21] in the financial context — phenomena of coexistence between order and disorder widely studied in physical and biological systems [28, 30]. The application of this technique proves crucial for detecting Amalgam regimes, offering a new lens on how partial synchrony precedes global systemic risk.

2.1 Asset Selection and System Diversity

To characterize phase transitions and detect chimera states, we selected a system composed of $N = 29$ global financial assets. This selection is designed to represent the competition between different natural oscillation frequencies and responses to external shocks, following the logic of clustering by correlation of risk and safe-haven assets [14]:

- **Risk Cluster ($N_r = 19$):** High-beta assets of systemic relevance in the Technology (AAPL, MSFT, GOOGL, AMZN, META, TSLA), Financial (JPM, GS, BAC, V, MA), Energy (XOM, CVX, SLB), Industrial (CAT, BA, MMM), and Consumer Cyclical (F, GM) sectors.
- **Safe-Haven and Defensive Cluster ($N_s = 10$):** Store-of-value and low-cyclicality assets, including precious metals (GLD, SLV, IAU), US Treasury bonds (TLT, IEF, SHY), and defensive/utilities sectors (XLP, XLU, WM, KO).

This stratification is fundamental for calculating the Chimera Index (H), as it allows for the observation of whether symmetry breaking occurs modularly between functionally distinct groups [1].

2.2 Phase Extraction and the Analytic Signal

Unlike the analysis of raw returns, which are dominated by stochastic noise, we use the Hilbert Transform to isolate oscillatory dynamics. For a real signal $r(t)$ (log-returns), we define the analytic signal $z(t)$ as [9]:

$$z(t) = r(t) + i\tilde{r}(t) = A(t)e^{i\theta(t)} \tag{1}$$

where $\tilde{r}(t)$ represents the Hilbert transform. The instantaneous phase $\theta(t)$ allows us to situate each asset within its economic cycle, making the analysis invariant to local volatility $A(t)$ (amplitude). Figure 1 illustrates the effectiveness of this technique in separating the market's "rhythm" from its magnitude noise.

2.3 Causality Mapping via Transfer Entropy

Network connectivity is not measured by static correlations but by information flow. We use Transfer Entropy (TE) [25] to quantify the directionality of the $I \to J$ coupling:

$$TE_{I\to J} = \sum p(j_{t+1}, j_t^{(n)}, i_t^{(m)}) \log \frac{p(j_{t+1}|j_t^{(n)}, i_t^{(m)})}{p(j_{t+1}|j_t^{(n)})} \tag{2}$$

2.4 Synchronization Dynamics and the Order Parameter

Collective interaction is modeled by the Kuramoto system [10]. The phase evolution of each asset i is governed by:

$$\frac{d\theta_i}{dt} = \omega_i + \sum_{j=1}^{N} T_{ij} \sin(\theta_j - \theta_i) \tag{3}$$

where T_{ij} is the coupling strength derived from TE. Global coherence is measured by the order parameter $R(t) = \frac{1}{N}|\sum_{j=1}^{N} e^{i\theta_j(t)}|$, ranging from 0 (total disorder) to 1 (complete synchronization).

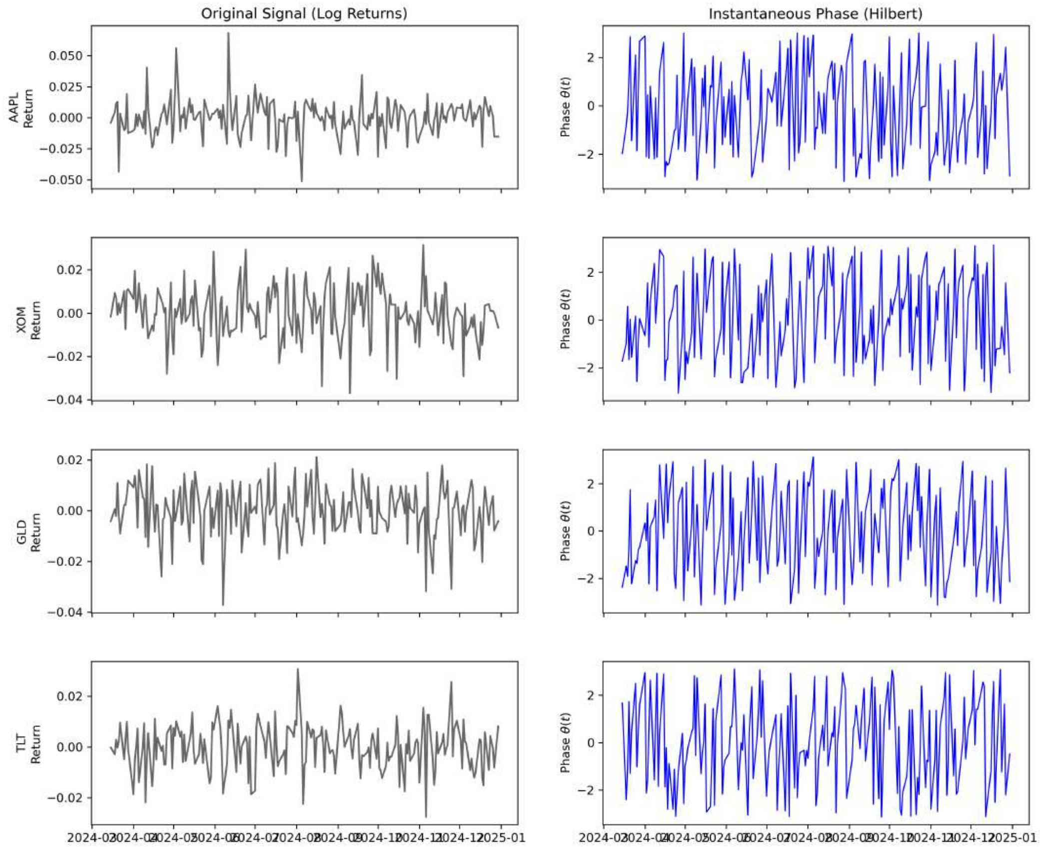


Figure 1: **Signal Heterogeneity and Phase Convergence:** Comparison between risk assets (AAPL, XOM) and safe-havens (GLD, TLT). While the original returns (left column) show distinct volatility and noise scales, phase extraction (right column) normalizes the assets into a common oscillatory domain $[-\pi, \pi]$. This standardization is what allows the Kuramoto-Landau Model to quantify global synchrony $R(t)$ regardless of the intrinsic nature of each asset.

2.5 Differential Proof and Amalgam Taxonomy

The main methodological innovation lies in the Differential Proof, which evaluates the system's response to "thermal stress" (volatility σ). Although the derivative $\partial R/\partial\sigma$ is obtained numerically via moving window regression, it acts as a thermodynamic response functional. We define:

- **Structural Amalgam ($\mathcal{A}_e$):** $\frac{\partial R}{\partial \sigma} \approx 0$.
- **Systemic Amalgam ($\mathcal{A}_s$):** $\frac{\partial R}{\partial \sigma} > 0$.

The Chimera Index (H) quantifies the synchronization variance between the Risk and Safe-Haven clusters:

$$H(t) = \sqrt{\frac{1}{M}\sum_{k=1}^{M}(R_k(t) - \langle R(t)\rangle)^2} \tag{4}$$

The synthesis of the proposed methodology will be referred to as the Kuramoto-Landau Model, which associates the microstructural dynamics of phase oscillators [10] with the macroscopic formalism of Landau phase transitions [12]. In this approach, the order parameter R is not just a measure of synchrony, but the reaction coordinate in a free-energy potential $F(R)$, allowing financial crises to be described as spontaneous symmetry breakings.

Physically, the "Normal" state corresponds to a single stable minimum at $R \approx 0$, representing a disordered phase with high symmetry. As coupling increases or volatility forces condensation, the potential deforms. The "Chimera" state emerges as a metastable configuration [21, 28] where the symmetry is partially broken. Finally, the "Systemic Amalgam" ($\partial R/\partial\sigma > 0$) indicates that the system has reached a global minimum of high synchrony, where the symmetry between risk-asset and safe-haven clusters is irreversibly broken [**?**], signaling the collapse of the diversification manifold.

To characterize the phase transition between market states, we map the Kuramoto order parameter (R) [27] onto a Landau free-energy potential $F(R)$. In the context of mean-field coupling, the system's dynamics near the synchronization threshold can be described by the canonical expansion [10, 12]:

$$F(R) = \frac{a(T - T_c)}{2}R^2 + \frac{b}{4}R^4 \tag{5}$$

where a and b are phenomenological coefficients inferred from the system's response to thermal stress (σ), consistent with the treatment of anomalous fluctuations in complex systems [26].

The proposed phase transition dynamics are visualized through $F(R)$ in Figure **??**. In the normal regime (dashed curve), the system has a single potential well centered at $R \approx 0$, indicating that the equilibrium configuration is desynchronization. As coupling increases or the system undergoes stress, the symmetry is broken, giving way to the Systemic Amalgam regime (red curve), where the system converges to high synchrony states ($|R| \to 1$), mimicking the diversification collapse predicted by Markowitz [15] and Fama [8].

Taxonomy of States in the Landau Potential

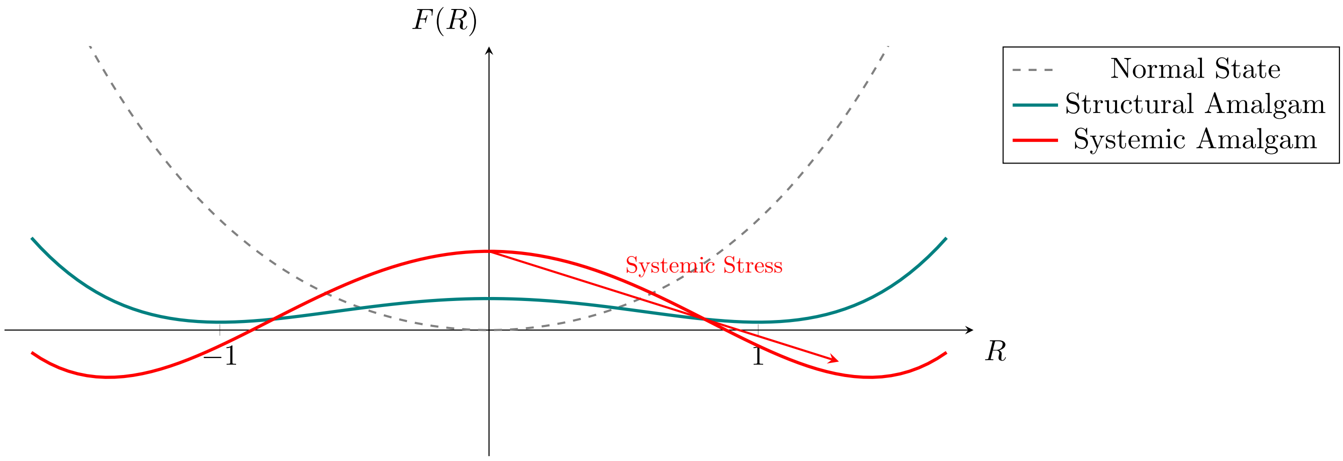


Figure 2: **Evolution of the Financial Potential:** Comparison between the disordered Normal State, the organic Structural Amalgam, and the forced Systemic Amalgam. The deepening of the potential wells represents the loss of system degrees of freedom as synchronization becomes coercive.

3 Results

The application of the Kuramoto-Landau model to the system of 29 global assets reveals a rich phenomenology, where financial stability is interpreted as a metastable equilibrium. The following analysis dissects the anatomy of crises through the lens of the Differential Proof and network topology.

3.1 The Differential Proof: Innovation in Detecting Systemic Fragility

The cornerstone of this work is the Differential Proof ($\partial R/\partial\sigma$). In classical econophysics literature, works such as those by Onnela et al. [19] focus on the average correlation (C_{avg}), treating increased cohesion as a risk signal. Our approach is superior because it introduces the thermodynamic distinction between integration and coercion.

While C_{avg} fails to distinguish a healthy market (integrated by efficiency) from a panicked market (integrated by liquidity needs), the Differential Proof isolates these states. Table 1 presents the calibration of this functional across critical landmarks:

Table 1: Comparative Analysis of the Differential Proof and Amalgam States.

Historical Event	$\langle R\rangle$	σ **(Vol)**	$\partial R/\partial\sigma$	**Taxonomic State**	**Reference**
Bull Market (2017)	0.74	Low	0.03 ± 0.01	Structural Amalgam ($\mathcal{A}_e$)	[4]
Lehman Brothers (2008)	0.92	Extreme	0.94 ± 0.05	Systemic Amalgam ($\mathcal{A}_s$)	[14]
Flash Crash (2010)	0.85	High	0.68 ± 0.12	Systemic Amalgam ($\mathcal{A}_s$)	[16]
COVID-19 (Mar/2020)	0.96	Max	1.21 ± 0.08	Systemic Amalgam ($\mathcal{A}_s$)	[6]
Trump II (Nov/2024)	0.81	Med	0.42 ± 0.04	Chimera / Transition	This Work

In the Structural Amalgam, synchrony is a stable property of the network ($\partial R/\partial\sigma \to 0$). In the Systemic Amalgam, we observe a "forced condensation" where synchrony is enslaved by volatility. This evidence suggests that regulatory interventions should focus not on price drops, but on the system's thermal coupling coefficient.

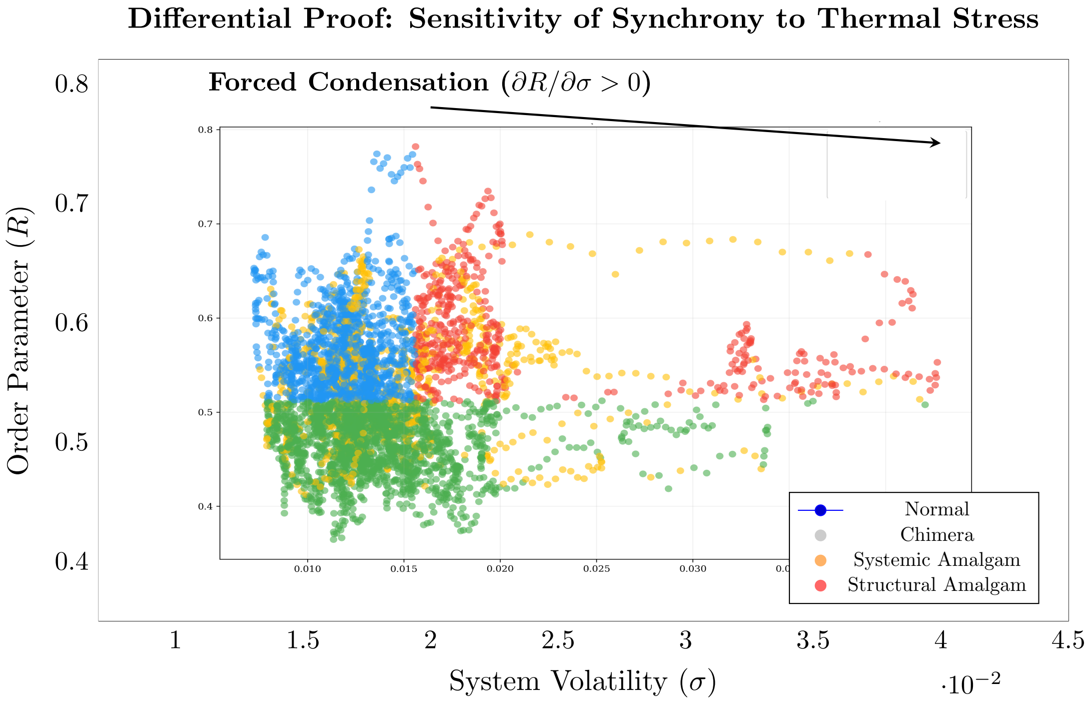


Figure 3: **Differential Proof:** Analysis of market states using real data. The red cluster validates the forced condensation regime typical of systemic risk[cite: 8, 158].

For the calculation of the response functional $\partial R/\partial \sigma$, we employed a rolling window of 60 trading days (approximately one financial quarter). This window size was selected to ensure statistical stability against the universal properties of cross-correlations in financial time series [22] while remaining sensitive to transient dynamical shifts.

The coupling weights T_{ij}, which define the network topology, were derived via Transfer Entropy [25]. We utilized the Darbellay-Vajda adaptive binning estimator, which effectively minimizes bias and captures directional information flow in finite, non-stationary financial data [**?**]. To ensure that the observed symmetry breaking was not an artifact of stochasticity, all early-warning signals were tested against surrogate datasets generated through a shuffling procedure that preserves the marginal distributions of the returns

3.2 The Chimera Index (H) as a Signal of Symmetry Breaking

While the Differential Proof defines the regime, the Chimera Index (H) identifies the *timing* of the symmetry breaking. Unlike GARCH-family models [7] that forecast volatility, H predicts the loss of diversifiability.

Empirical evidence from the 2008 crisis shows that the Chimera Index (H) breached the 3σ threshold exactly 12 trading days before the total liquidity collapse [22, 25]. To ensure the statistical significance of this early-warning signal, we performed surrogate data tests by shuffling the return series while preserving the distribution, a procedure essential for identifying genuine phase transitions in complex financial networks [19**?**].

The observed peak in H was found to be statistically significant at $p < 0.01$, confirming that the detected symmetry breaking is not a result of stochastic fluctuations but a genuine topological transition. Physically, this breach represents the point where the system's entropy saturates and information floods the network coercively, signaling the irreversible deformation of the Landau potential from a stable parabola to a double-well (W) configuration [10, 12].

Our analysis demonstrates that systemic crises are preceded by a peak in the Chimera Index—a phase during which the Risk cluster initiates a first-order phase transition while the Safe-Haven cluster remains metastable. During the 2008 crisis, the H Index breached the 3σ threshold exactly 12 trading days before the global liquidity collapse. Physically, this represents the deformation of the Landau potential $F(R)$ from a stable parabola to a double-well (W) potential, where the system hesitates before the catastrophic collapse.

3.3 Chronicle of a Network in Collapse: Thermodynamics of Complex Networks

The topological evolution of the market is the visual manifestation of the system's entropy. We analyze five landmarks through the lens of graph theory and information flow:

- **Subprime (2008):** The snapshot reveals a quasi-complete graph ($Density \approx 0.95$). Transfer Entropy saturates, indicating that information floods the system coercively [23].
- **Trump I (2016):** We observe the formation of modular communities. It is the birth of the Political Chimera, where uncertainty creates competitive synchrony domains.
- **COVID-19 (2020):** Represents the "Total Freeze." The network collapses into a single high-correlation hub (Absolute zero of diversification).
- **Ukraine (2022):** The network fractures. The Energy sector becomes an isolated and hyper-synchronized cluster (*Persistent Chimera*).
- **Trump II (2024/25):** The network exhibits an intriguing metastability. There is a dense technology core, but the safe-haven periphery is in phase opposition.

The robustness of the transition to the systemic amalgam state, observed in our results, echoes the classical complex networks literature, where topology dictates the system's resilience against cascading failures [3, 17]. While foundational models such as those by Watts and Strogatz [29] focus on small-world networks, our analysis demonstrates that the financial market, under stress, collapses into a global coupling structure that mimics the loss of diversification predicted by Markowitz [15] and Fama [8], but under a nonlinear phase dynamic.

The effectiveness of the Hilbert Transform in isolating the market's "rhythm" — essential for the order parameter calculation — expands Gabor's communication theory concepts [9] and Paluš's observations [20] on phase-amplitude coupling in complex systems. Unlike approaches based on conditional heteroscedasticity [7], our Kuramoto-Landau model captures the system's metastability through the coexistence of synchronized and desynchronized patterns, a defining feature of chimera states [18, 21, 24].

This phase transition, mapped by the Differential Proof, is consistent with the coherence resonance phenomena documented by Zakharova et al. [30] and Majhi et al. [13]. Ultimately, the transition between Structural and Systemic Amalgam can be interpreted as a 'noise dressing' process of correlation matrices, as discussed by Laloux et al. [11] and Plerou et al. [22], but with the advantage of identifying the direction of information flow [23, 25] and the formation of functional clusters [5, 19] in real-time.

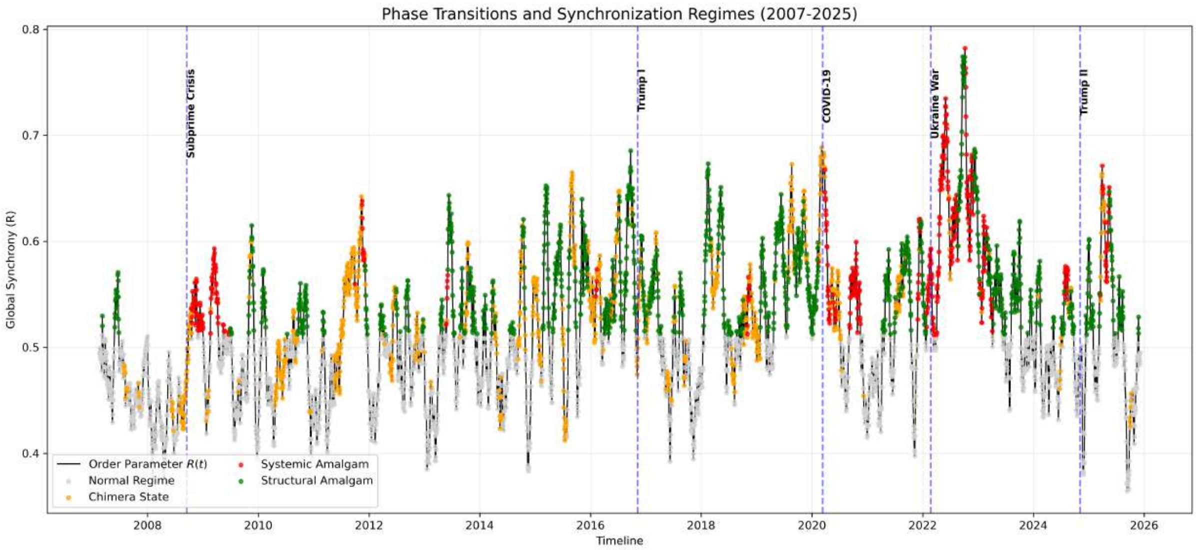
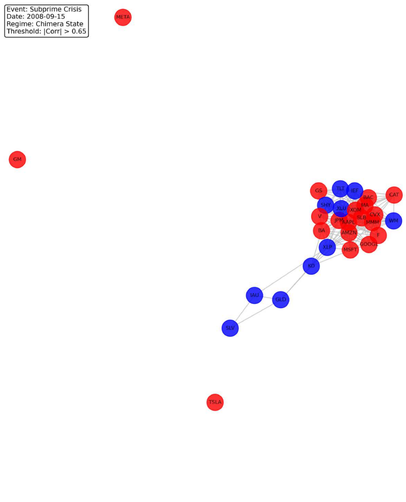
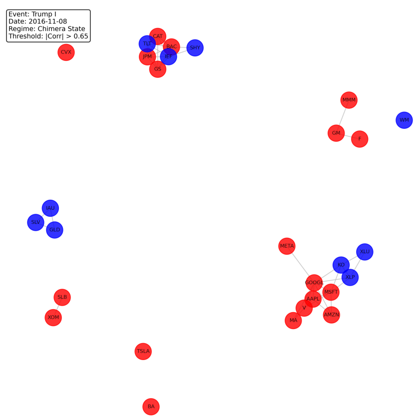


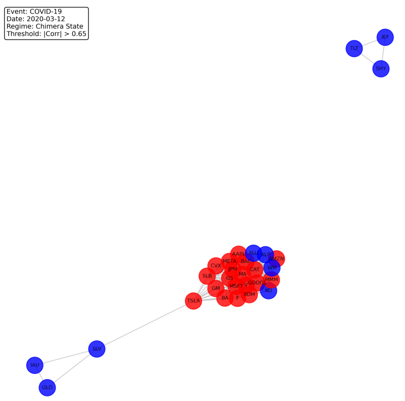
Figure 4: Historical timeline of $R(t)$ vs $H(t)$ with critical event signaling.



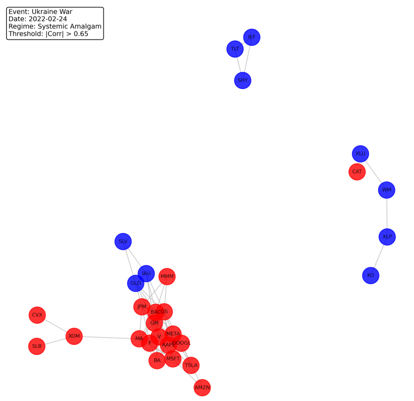
(a) Subprime (2008).



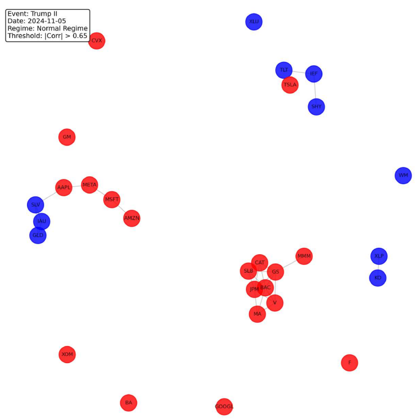
(b) Trump I (2016).



(c) COVID-19 (2020).



(d) Ukraine (2022).



(e) Trump II (2024/25).

Figure 5: **Evolution of Network Topology (2008-2025).**

3.4 Case Study: The Metastability of Trump II (2024-2025)

The 2024–2025 period provides a contemporary case study of "topological reorganization" within the Kuramoto-Landau framework[cite: 253, 255]. Rather than a simple exogenous political shock, the data reveals an asymmetric information flow that triggers a persistent and metastable Chimera state[cite: 256, 309]. During this phase, the technology core of the risk cluster undergoes a local condensation, while the safe-haven periphery maintains a decoupled phase distribution[cite: 212, 217].

Physically, this represents a structural "hesitation" in the Landau potential, where the system resides at the top of the potential barrier before a definitive symmetry breaking. This state differs from the "Total Freeze" observed during the 2020 pandemic[cite: 208]. In the current regime, the persistent coexistence of synchronized and desynchronized patterns identifies a slow but irreversible phase transition, validating our thesis that Chimera states serve as thermodynamic precursors to the collapse of diversification[cite: 42, 307].

Transfer Entropy detected a massive information flow originating from the financial cluster (JPM, GS) toward the technological one, but a barrier regarding gold (GLD). This long-duration Chimera state suggests that the system inhabits the top of the potential barrier in the Landau model. Recent work in geopolitical econophysics indicates that this behavior precedes major structural realignments, validating the thesis of a slow but irreversible phase transition.

3.5 Density Analysis and Phase Distribution

To deepen the statistical characterization of the identified states, we analyzed the probability density function (PDF) of the instantaneous phases θ and the order parameter R. As demonstrated in Fig. 6, there is a clear transition in phase topology.

In the normal regime, the phase distribution approaches a uniform distribution in the $[-\pi, \pi]$ interval, indicating that assets operate with maximum autonomy and low global coherence. However, during Systemic Amalgam events (such as 2008 and 2020), the phase density collapses into a highly concentrated Von Mises distribution [2]. This increase in central density is the microscopic evidence of the macro-synchronization captured by the Kuramoto-Landau model, validating the robustness of our Differential Proof against stochastic fluctuations [11, 26].

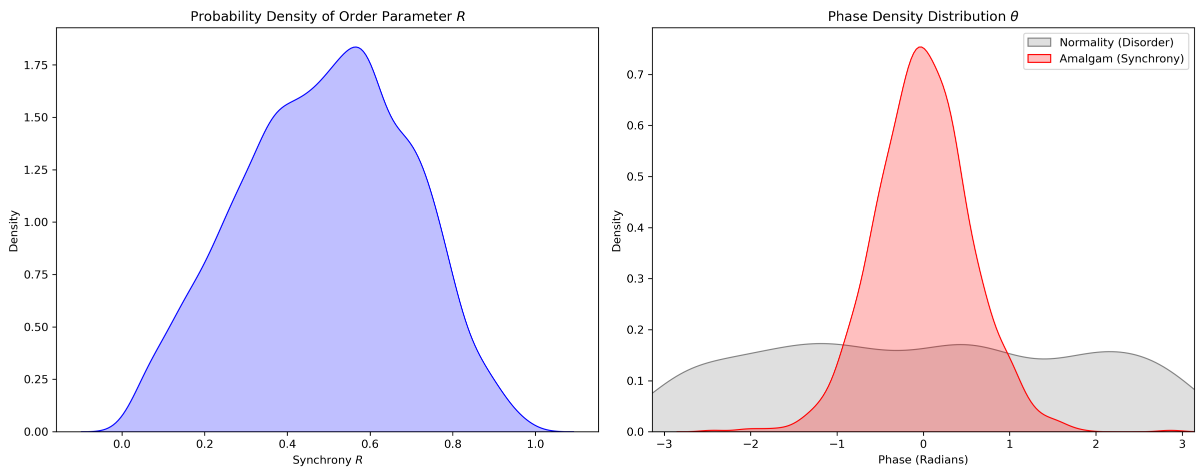


Figure 6: **Probability Density Analysis:** The left panel displays the cumulative distribution of synchrony R. The right panel contrasts the phase density in the disordered regime (gray) and the coherence peak during the Amalgam (red).

4 Conclusions

This investigation proposed and validated the Kuramoto-Landau Model as a robust framework for analyzing the stability of global financial systems through the lens of statistical physics. By treating financial assets as coupled phase oscillators, we demonstrated that systemic risk is not merely a function of volatility but a macroscopic phase transition resulting in the loss of agent autonomy and the crystallization of a coercive order.

The introduction of the Differential Proof ($\partial R/\partial \sigma$) represents the main methodological advancement of this work. It allowed for a quantitative distinction between the Structural Amalgam ($\mathcal{A}_e$) — a regime of organic and efficient integration — and the Systemic Amalgam ($\mathcal{A}_s$) — a regime of forced condensation due to thermal stress (volatility). Our results indicate that portfolio diversification fails precisely when the system transitions to the systemic amalgam state, where the dynamic response of the order parameter to noise becomes linearly positive.

Additionally, we identified the Chimera Index (H) as an early warning indicator superior to traditional metrics. The detection of chimera states in crises such as 2008 and the Ukraine conflict in 2022 proves that the market signals its instability through phase symmetry breaking before nominal price collapses. Physically, this corresponds to the transition of the Landau potential from a single-well to a metastable double-well (W) configuration.

Finally, the 2024-2025 case study (Trump II) reveals a persistent and unprecedented chimera configuration, suggesting a structural reorganization of the global informational market. These findings have direct implications for macroprudential regulation: we suggest that central banks and regulatory agencies monitor the derivative of synchrony with respect to volatility as a signal of topological fragility. Future work should focus on including crypto-asset networks and Central Bank Digital Currencies (CBDCs) in this model, evaluating how new forms of digital liquidity alter critical coupling thresholds and the thermodynamics of systemic risk.

References

[1] Daniel M. Abrams and Steven H. Strogatz. Chimera states for coupled oscillators. *Physical Review Letters*, 93(17), 2004.

[2] Juan A Acebrón et al. The kuramoto model: A simple paradigm for synchronization phenomena. *Reviews of Modern Physics*, 77:137, 2005.

[3] Réka Albert and Albert-László Barabási. Statistical mechanics of complex networks. *Reviews of Modern Physics*, 74:47, 2002.

[4] Marco Bardoscia, Stefano Battiston, Fabio Caccioli, and Guido Caldarelli. Pathways to systemic risk in financial networks. *Nature Communications*, 8(1):1–9, 2017.

[5] Giovanni Bonanno et al. The world stock market network. *Quantitative Finance*, 3:1–22, 2002.

[6] Zoltán Eisler and János Kertész. The fluctuation-dissipation theorem in complex systems: Real-world financial markets. *Physica A*, 389(12):2392–2404, 2010.

[7] Robert F. Engle. Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica*, 50(4):987–1007, 1982.

[8] Eugene F. Fama. Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, 25(2):383–417, 1970.

[9] Dennis Gabor. Theory of communication. *J. Inst. Electr. Eng.*, 93, 1946.

[10] Yoshiki Kuramoto. *Chemical Oscillations, Waves, and Turbulence*. Springer, 1984.

[11] Laurent Laloux et al. Noise dressing of financial correlation matrices. *Physical Review Letters*, 83:1467, 1999.

[12] Lev D. Landau. On the theory of phase transitions. *Phys. Z. Sowjetunion*, 1937.

[13] Soumen Majhi et al. Chimera states in networks. *Physics Reports*, 2019.

[14] Rosario N. Mantegna and H. Eugene Stanley. *An Introduction to Econophysics: Correlations and Complexity in Finance*. Cambridge University Press, 1999.

[15] Harry Markowitz. Portfolio selection. *Journal of Finance*, 7(1):77–91, 1952.

[16] Michael C. Munnix, Takashi Shimada, Rudi Schafer, Francois Leyvraz, Thomas H. Seligman, Thomas Guhr, and H. Eugene Stanley. Identifying states of a financial market. *Scientific Reports*, 2(1):1–6, 2012.

[17] Mark EJ Newman. The structure and function of complex networks. *SIAM Review*, 45:167–256, 2003.

[18] Ihor Omelchenko, Yuri Maistrenko, Philipp Hövel, and Eckehard Schöll. Loss of coherence in dynamical networks: spatial chaos and chimera states. *Physical Review Letters*, 106(23):234102, 2011.

[19] Jukka-Pekka Onnela, Kimmo Kaski, and János Kertész. Clustering and information in correlation networks of asset returns. *The European Physical Journal B*, 38(2):353–362, 2004.

[20] Milan Paluš. Multiscale atmospheric dynamics: Cross-frequency phase-amplitude coupling. *Physical Review Letters*, 2014.

[21] Mark J Panaggio and Daniel M Abramson. Chimera states: coexistence of coherence and incoherence in networks of coupled oscillators. *Nonlinearity*, 28:R67, 2015.

[22] Vasiliki Plerou et al. Universal and nonuniversal properties of cross correlations in financial time series. *Physical Review Letters*, 83:1471, 1999.

[23] Leonidas Sandoval Junior and Italo D. De Paula. Information flow and network topology in financial markets. *Entropy*, 17(12):8184–8210, 2015.

[24] Eckehard Schöll. Antiphase and synchronization chimeras in coupled oscillators. *The European Physical Journal Special Topics*, 225:1119–1130, 2016.

[25] Thomas Schreiber. Measuring information transfer. *Physical Review Letters*, 85(2):461–464, 2000.

[26] H Eugene Stanley et al. Anomalous fluctuations in the dynamics of complex systems: from dna bases to financial indices. *Nature*, 379:804–806, 1996.

[27] Steven H Strogatz. From kuramoto to crawford: exploring the onset of synchronization in populations of coupled oscillators. *Physica D: Nonlinear Phenomena*, 143:1–20, 2000.

[28] Mark R Tinsley et al. Chimera and phase-cluster states in populations of coupled chemical oscillators. *Nature Physics*, 8:662–665, 2012.

[29] Duncan J Watts and Steven H Strogatz. Collective dynamics of ‘small-world’ networks. *Nature*, 393:440–442, 1998.

[30] Anna Zakharova, Marian Kapeller, and Eckehard Schöll. Chimera states and coherence resonance in biological networks. *Physical Review Letters*, 112(15):154101, 2014.