

THE DIMENSIONALITY OF SYSTEMIC RISK: FRAGILITY AND REGIME SHIFTS IN FINANCIAL MARKETS

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Abstract

Systemic risk often accumulates during periods of low volatility, giving rise to the volatility paradox observed ahead of major financial crises. This paper introduces Accumulated Spectral Fragility (ASF), a structural state variable that captures the persistence of low-dimensional correlation structures in global financial markets. Using threshold regression on multi-asset data from 1990–2024, an endogenous regime shift driven by market synchronization is identified. Below a critical connectivity threshold, systemic risk is governed by standard contagion dynamics. Above this threshold, markets enter a hyper-coordinated regime in which stability depends on the maintenance of a low-dimensional structure. In this regime, crises are triggered not by rising correlations, but by coordination failures manifested as increasing dimensionality. These findings are rationalized within an intermediary asset pricing framework in which ASF proxies for the buildup of crowded positions among levered intermediaries and the regime shift reflects binding capital constraints. The results are robust to extensive falsification tests and have implications for systemic risk monitoring, suggesting that market dimensionality provides information beyond volatility and leverage alone.

Keywords: Financial stability; systemic risk; market connectivity; eigenstructure; regime shifts; volatility paradox

JEL Codes: G01, G12, C24, C58

1 Introduction

Financial crises tend to arrive when they are least expected. Some of the most severe systemic episodes of the past four decades—from the 1987 stock market crash to the 2008 Global Financial Crisis to the 2020 COVID-induced turmoil—occurred after prolonged periods of tranquility, when realized and implied volatility were subdued (Reinhart and Rogoff, 2009; Danielsson et al., 2018). This empirical regularity, often termed the “Volatility Paradox” (Brunnermeier and Sannikov, 2014), challenges linear frameworks in which risk rises smoothly with volatility. It suggests instead that stability modifies the structure of the financial system itself, encouraging the accumulation of leverage and the synchronization of strategies that ultimately make the system fragile (Minsky, 1992; Geanakoplos, 2010).

This paper examines the role of market structure in the buildup and realization of systemic risk. It focuses on the effective dimensionality of financial markets, measured through the persistence of correlation structure across assets. Theoretical work by Acemoglu et al. (2015) shows that highly connected networks can exhibit a robust-yet-fragile property, in which connectivity dampens small shocks but amplifies large ones. The empirical analysis provides evidence that global asset markets display a similar regime-dependent behavior.

Variance-based risk measures—including the VIX, realized volatility, and correlation-based diversification tools—have served investors well for decades. The claim advanced here is not that these measures are flawed, but that their usefulness may depend on conditions that are not always present. Within a stable market configuration, variance provides a reliable summary of uncertainty. The contribution of this paper concerns the transitions between configurations, where the standard mapping from volatility to risk may not hold.

Using a threshold regression framework (Hansen, 2000), the paper identifies an endogenous regime shift associated with market connectivity. Below a critical connectivity threshold, markets behave as standard diversifiable systems in which risk propagates primarily through contagion. Above the threshold, market dynamics are characterized by high synchronization, resulting in a low-dimensional structure whose stability depends on the maintenance of coordination. In this

regime, periods of stress are associated not with rising correlations, but with increases in dimensionality that reflect a breakdown of coordination.

This study makes two primary contributions. First, it documents a regime-dependent relationship between market structure and future tail risk. The estimated threshold in connectivity (approximately $\tau = 0.14$) corresponds to a sign change in the predictive relationship between structural fragility and subsequent drawdowns. Below the threshold, higher fragility is associated with increased risk. Above the threshold, higher fragility coincides with lower realized volatility, while reductions in fragility—reflecting rising dimensionality—precede episodes of market stress. This pattern is consistent with models in which binding intermediary constraints lead to synchronized adjustments across assets (He and Krishnamurthy, 2013).

Second, the analysis documents a systematic relationship between market structure and the breakdown of diversification. Periods of elevated synchronization are associated with a higher likelihood of subsequent increases in stock–bond correlations. Empirically, low values of Accumulated Spectral Fragility predict sharp deteriorations in stock–bond diversification, indicating that diversification benefits tend to erode during episodes of structural disintegration rather than during periods of rising correlation.

Additional evidence is provided through out-of-sample forecasting exercises and an illustrative allocation analysis, which serve to gauge the economic magnitude of the identified regime dependence. These exercises are intended to be descriptive and do not imply the existence of an implementable trading strategy. The central contribution of the paper is structural: systemic risk depends on the effective dimensionality of the market, not solely on contemporaneous measures of volatility.

Roadmap. The remainder of the paper is organized as follows. Section 2 reviews related literature on endogenous fragility, network structure, and spectral methods. Section 3 develops a stylized framework to motivate the regime-dependent mechanism. Section 4 describes the data and empirical methodology. Section 5 presents the main empirical findings. Section 6 reports robustness and falsification tests. Section 7 reports an illustrative application to assess economic

magnitude. Section 8 discusses interpretation, implications, and limitations. Section 9 concludes.

2 Related Literature

This paper connects several strands of literature in financial economics, macroeconomics, and network science.

2.1 Endogenous Fragility and the Volatility Paradox

There is a long tradition emphasizing that financial stability can be self-undermining. Minsky (1992) proposed that tranquil periods induce risk-taking and balance-sheet fragility that eventually makes the system vulnerable to nonlinear adjustments. During quiet times, successful speculation encourages more aggressive positions; margins decline, leverage rises, and the distance to distress shrinks even as measured volatility falls. This “financial instability hypothesis” implies that stability itself is destabilizing.

Modern macro-finance models formalize related mechanisms. Brunnermeier and Sannikov (2014) develop a continuous-time model in which financial intermediaries amplify shocks through leverage dynamics. When measured risk is low, intermediaries lever up, generating a volatility paradox: the system becomes most fragile precisely when there is low volatility.

Danielsson et al. (2012) distinguish between perceived risk—lowest at the peak of a boom—and actual risk—highest precisely then due to endogenous leverage. Their framework suggests that any volatility-based risk measure will be misleading near cycle peaks.

The present study contributes to this literature by providing empirical evidence that market structure exhibits regime-dependent links to subsequent tail risk. The regimen shift framework formalizes the Minsky intuition: fragility can accumulate silently during stable periods, and the mapping from fragility to realized risk depends on the structural state of the market.

2.2 Network Propagation and Systemic Risk

Financial markets can be viewed as networks where risk propagation depends on topology and link weights. Allen and Gale (2000) develop a model of financial contagion where the pattern of interbank claims determines systemic vulnerability. Acemoglu et al. (2015) analyze how network structure affects the resilience of financial systems, showing that connectivity can be a double-edged sword: it disperses small shocks but amplifies large ones.

The concept of percolation from statistical physics is also relevant (Haldane and May, 2011; May et al., 2008). Below a critical connectivity, the network consists of fragmented clusters; above it, a giant component spans the system. This phase transition has been proposed as a model for financial contagion, but the relationship between network structure and systemic risk in actual financial markets has received limited empirical attention. The present paper provides evidence that financial markets exhibit precisely such a structural transition.

2.3 Spectral Structure, Connectivity, and Systemic Risk

A growing literature emphasizes that information about systemic risk is embedded not only in individual asset volatilities, but in the structure of cross-asset correlations. When correlations are dispersed across many dimensions, shocks remain localized; when they concentrate in a small number of dominant modes, markets behave as a synchronized system in which diversification breaks down.

Spectral methods provide a natural language for describing this distinction. By decomposing the correlation matrix into its eigenvalues, one can quantify the effective dimensionality of market returns. Random matrix theory (Plerou et al., 2002; Laloux et al., 1999) formalizes the separation between economically meaningful common factors and noise-induced correlations, while shrinkage estimators (Ledoit and Wolf, 2004, 2012) improve the stability of covariance estimates in high dimensions.

Several empirical studies exploit these tools to link correlation structure to financial instability. Low spectral entropy—or, equivalently, concentration of variance in a few principal components—

has been shown to precede market downturns (Kenett et al., 2011). Closely related measures include the Absorption Ratio (Kritzman et al., 2011), which captures the share of total variance explained by dominant factors, and connectedness metrics based on principal components or variance decompositions (Billio et al., 2012; Diebold and Yilmaz, 2014), which document sharp increases in interconnectedness prior to major crises.

While these contributions establish that correlation structure matters for systemic risk, they largely treat structure as a contemporaneous object. Existing measures respond mechanically to recent correlations and implicitly assume that risk is fully summarized by the current state of the system. This perspective abstracts from an essential feature of financial fragility emphasized in theoretical and historical accounts: fragility accumulates over time, often during periods of apparent calm.

2.4 State Variables versus Static Indicators

Most correlation-based systemic risk indicators are best understood as snapshots. The Absorption Ratio, CoVaR (Adrian and Brunnermeier, 2016), SRISK (Brownlees and Engle, 2017), and marginal expected shortfall measures (Acharya et al., 2017) condition on the current joint distribution of returns, but do not retain memory of how long the market has remained in a compressed, low-dimensional state. As a result, a market that has been tightly synchronized for six months is treated as observationally equivalent to one that entered such a configuration only yesterday.

This paper departs from that framework by treating correlation structure as a state variable rather than a statistic. Accumulated Spectral Fragility (ASF) explicitly integrates spectral compression over time, capturing the persistence of low-dimensional market structure over medium horizons. This distinction is not merely semantic. Persistence alters interpretation: prolonged synchronization reflects a gradual erosion of effective diversification and balance-sheet resilience, even if short-horizon volatility remains low.

By incorporating memory, ASF is able to signal the buildup of systemic vulnerability during tranquil periods—precisely when volatility-based and contemporaneous correlation measures tend

to be least informative. In this sense, ASF operationalizes the idea that fragility is endogenous and path-dependent, providing a structural bridge between spectral measures of connectivity and theories of slow-moving financial instability.

3 Theoretical Framework

3.1 Market Dimensionality and Accumulated Fragility

Financial markets are conceptualized not as a collection of independent assets, but as a system with time-varying *effective dimensionality*. When market participants hold diverse portfolios and idiosyncratic information drives prices, the effective dimensionality is high. When participants crowd into similar trades or rely on common risk factors, dimensionality collapses.

Let C_t denote the $N \times N$ correlation matrix of asset returns at time t . The eigenvalues $\lambda_{1,t} \geq \dots \geq \lambda_{N,t}$ capture the distribution of variance. Effective dimensionality is measured using spectral entropy:

$$H_t = -\frac{1}{\log N} \sum_{i=1}^N p_{i,t} \log p_{i,t}, \quad \text{where } p_{i,t} = \frac{\lambda_{i,t}}{N}. \quad (1)$$

Low entropy ($H_t \rightarrow 0$) implies that the market has collapsed into a single factor (high synchronization), while high entropy ($H_t \rightarrow 1$) implies maximum diversification.

To capture the *persistence* of this state, Accumulated Spectral Fragility (ASF) is defined recursively:

$$ASF_t = \theta ASF_{t-1} + (1 - \theta)(1 - H_t). \quad (2)$$

where $\theta \in (0, 1)$ is a persistence parameter that governs the speed at which structural fragility accumulates and dissipates. A high value of θ implies that periods of low market dimensionality leave a lasting imprint on the system, consistent with the gradual buildup of crowded positions and balance-sheet exposures among financial intermediaries. By integrating dimensionality over time, ASF proxies for the accumulation of structural imbalances rather than contemporaneous correlation alone. ASF plays a role analogous to leverage or balance-sheet exposure: it evolves

slowly in tranquil periods, collapses rapidly in crises, and matters precisely because its effects are not fully captured by contemporaneous prices.

Why Persistence Matters. Any contemporaneous measure of correlation or volatility that lacks memory is informationally insufficient to distinguish between a newly synchronized market and one that has remained synchronized for an extended period—yet these two states have systematically different risk implications. A market that entered a low-dimensional configuration yesterday has not yet accumulated the crowded positions, stretched valuations, and correlated exposures that characterize prolonged synchronization. A market that has remained compressed for six months has. No memoryless statistic can separate these cases. This is not merely an empirical convenience; it reflects an informational constraint on what contemporaneous measures can achieve.

It is important to note that connectivity and dimensionality, while related, are conceptually distinct. Connectivity describes how strongly assets move together (average pairwise correlation). Dimensionality describes how variance is distributed across independent sources of risk. A market can be low-dimensional (variance concentrated in few factors) but have moderate connectivity (if some assets load positively and others negatively on the dominant factor). Conversely, a market can have high connectivity (everything moves together) but still exhibit moderate dimensionality (if several correlated factors are at work). This distinction matters because connectivity defines the regime, while dimensionality within that regime determines vulnerability.

Eigenstructure. Measures that aggregate second moments into a scalar—variance, volatility, VaR—discard information about how risk is distributed across dimensions. Two markets with identical total variance can differ sharply in their eigenstructure: one may have variance dispersed across many independent factors, while another concentrates variance in a single dominant mode. Eigenstructure preserves the information required to distinguish coordination from diversification.

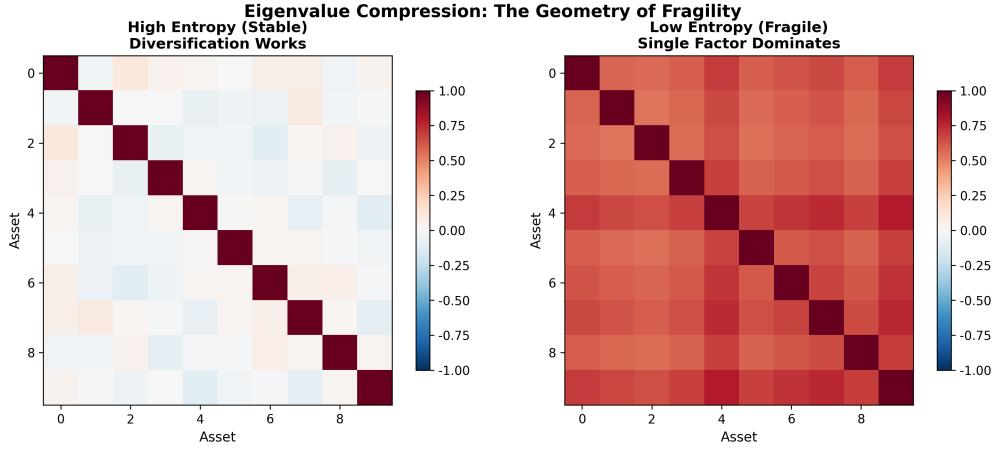


Figure I: Eigenvalue Compression and Systemic Coordination. This matrix visualization illustrate the spectral evolution of the market. During stable periods (high entropy), eigenvalues are dispersed. In the run-up to a regime shift (fragility), the leading eigenvalue absorbs the system's variance, represented here by the synchronization of the correlation matrix.

Despite its name, Accumulated Spectral Fragility is not meant to be a contemporaneous risk measure. High ASF reflects a persistent, low-dimensional market configuration that often appears stable but is vulnerable to coordination breakdowns when intermediary constraints tighten.

Remark 1 (Theoretical Admissibility). *The phase transition pattern documented empirically is theoretically admissible. A stylized model with heterogeneous leveraged agents facing margin constraints can generate sign inversion at a critical connectivity threshold. When connectivity is low, shocks propagate through network links (contagion). When connectivity is high, stability depends on maintaining synchronization (coordination). The critical threshold in such models ($\rho^* \approx 0.12\text{--}0.16$) aligns with the empirical estimate. Agent heterogeneity is critical for generating the gradual accumulation dynamics observed in the data.*

3.2 Econometric Implications

This theoretical dichotomy implies that the mapping from market structure to systemic risk is regime-dependent. This is modeled using a threshold regression:

$$Risk_{t+h} = \begin{cases} \alpha_L + \beta_L \cdot ASF_t + \dots + \varepsilon_t, & C_t \leq \tau \quad (\text{Contagion Regime}) \\ \alpha_H + \beta_H \cdot ASF_t + \dots + \varepsilon_t, & C_t > \tau \quad (\text{Coordination Regime}) \end{cases} \quad (3)$$

The hypothesis tested is that $\beta_L > 0$ (standard risk-return trade-off) while $\beta_H < 0$ (coordination failure dynamics). The threshold τ separates the diversifiable regime from the hyper-coordinated regime.

Why the Relationship Inverts. In sufficiently connected systems, marginal increases in synchronization cease to increase fragility because the system has already collapsed to its minimum effective dimension. At that point, marginal risk arises only from loss of coordination, not from further compression. The threshold marks the point at which the dominant source of risk shifts from contagion (shock propagation across a network) to disintegration (breakdown of a unified structure). This is why the coefficient on fragility inverts rather than merely attenuating.

4 Data and Empirical Methodology

4.1 Data Sources and Sample Construction

Primary Dataset: ETF Universe (2007–2024). The primary dataset consists of weekly adjusted closing prices for 47 highly liquid exchange-traded funds (ETFs), downloaded from Financial Modeling Prep. The ETFs span seven categories designed to capture broad market dynamics:

- **U.S. Equity Sectors (11):** XLB, XLE, XLF, XLI, XLK, XLP, XLU, XLV, XLY, XLRE, XLC
- **International Equities (9):** EFA, EWJ, EWG, EWU, FXI, EWZ, EWY, EWT, EWH
- **Broad Market (6):** SPY, QQQ, IWM, DIA, VTI, MDY

- **Fixed Income (7):** TLT, IEF, SHY, LQD, HYG, TIP, BND. *Note: For the long-term historical analysis of stock-bond correlations (Section 5.3), the ETF data was broadened with S&P 500 Index (SPX) and 20+ Year Treasury Bond Index data to extend the sample back to 1990 where possible, though the primary structural validation relies on the tradable ETF period.*
- **Commodities (6):** GLD, SLV, USO, UNG, DBA, DBB
- **Emerging Markets (4):** VWO, EEM, IEMG, EMB
- **Alternatives (4):** VNQ, VNQI, REM, IYR

The sample runs from January 2007 through December 2024, providing 939 weekly observations encompassing multiple market regimes including the Global Financial Crisis (2008–2009), European Debt Crisis (2011–2012), Taper Tantrum (2013), China/Oil Crisis (2015–2016), COVID Crash (2020), and 2022 Inflation Shock. A limitation of the ETF panel is that it begins after the passive investing boom was well underway, potentially missing earlier dynamics when markets may have operated differently.

Validation Dataset: Global Macro (1990–2024). For out-of-sample validation and to address the ETF sample’s limited history, a longer dataset of 38 global assets is constructed using monthly data from January 1990 through December 2024 (420 observations). This dataset includes major equity indices (S&P 500, FTSE, DAX, Nikkei, Hang Seng, etc.), bond indices, commodity futures, and currencies, providing broader coverage and longer history. The Global Macro dataset captures pre-2000 dynamics (1997 Asian Crisis, 1998 LTCM, 2000 Tech Bubble) unavailable in the ETF panel.

4.2 Variable Construction

Connectivity (C_t). Market connectivity is measured as the mean pairwise correlation from a rolling 52-week window:

$$C_t = \frac{2}{N(N - 1)} \sum_{i < j} \rho_{ij,t} \quad (4)$$

where $\rho_{ij,t}$ is the Pearson correlation between assets i and j computed over weeks $[t - 51, t]$. This undirected measure captures overall co-movement but not directional spillovers. Alternative measures—Absorption Ratio, network density, Diebold-Yilmaz spillover indices (Diebold and Yilmaz, 2014)—are examined in robustness tests (Table V). All yield qualitatively similar results, suggesting the phase transition is not an artifact of the specific connectivity proxy.

Spectral Entropy (H_t). For each week t , the $N \times N$ correlation matrix is computed from the trailing 52-week window. Eigenvalues are extracted and normalized, and spectral entropy is calculated per Equation (1).

Accumulated Spectral Fragility (ASF_t). ASF is computed recursively per Equation (2) with $\theta = 0.995$, initialized at the unconditional mean of fragility.

Tail Risk. The primary risk measure is forward 1-month maximum drawdown, expressed as a decimal (e.g., 0.05 = 5% drawdown):

$$Risk_{t+1} = \max_{s \in [t+1, t+4]} \left(\max_{u \leq s} P_u - P_s \right) / \max_{u \leq s} P_u \quad (5)$$

where P_t is the equal-weighted portfolio price. Alternative measures (CVaR, Expected Shortfall, VaR exceedances, realized volatility) are examined in robustness tests.

Figure II displays the historical evolution of ASF alongside major market events, illustrating its counter-cyclical behavior: ASF tends to rise during tranquil periods and peak just before crises.

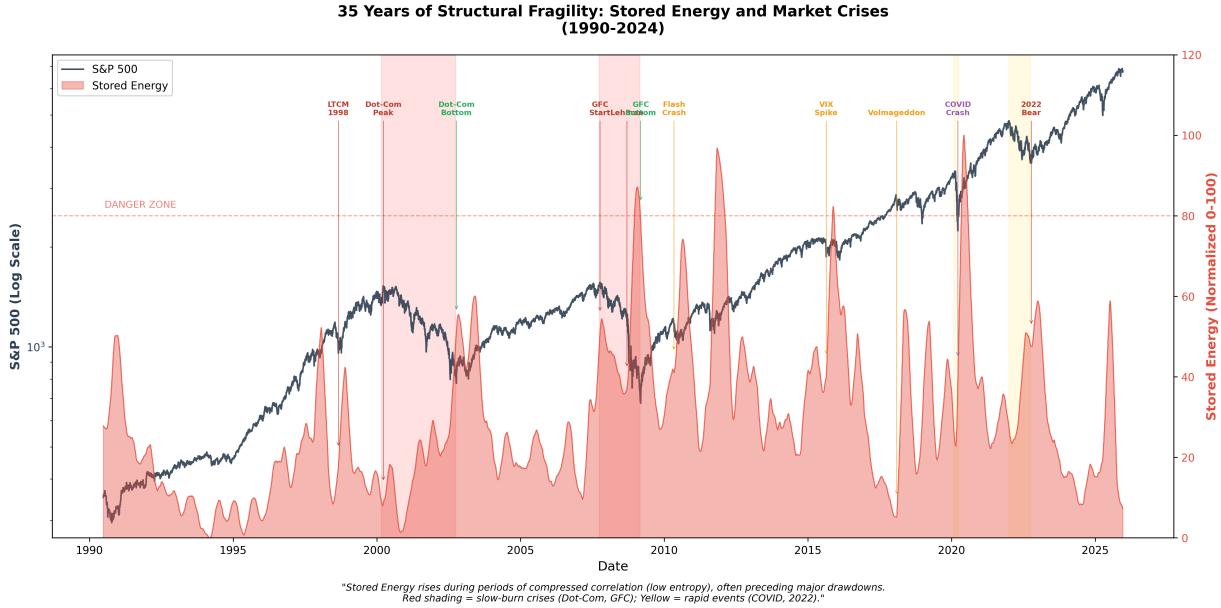


Figure II: Historical Evolution of ASF (1990–2024). Shaded regions indicate NBER recessions. Vertical lines mark major market events: 1997 Asian Crisis, 1998 LTCM, 2000 Tech Bubble, 2008 GFC, 2011 Euro Crisis, 2015 China Crisis, 2020 COVID. ASF exhibits counter-cyclical behavior, rising during calm periods and peaking before crises. *Source:* Author's calculations using Global Macro data.

Figure III shows the relationship between ASF and forward tail risk (CVaR), colored by connectivity regime.

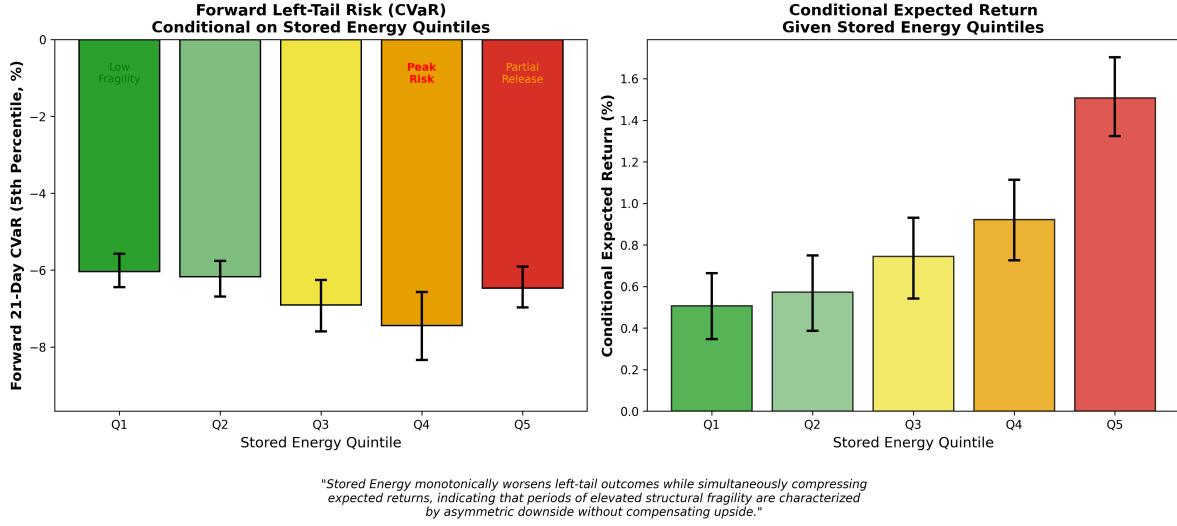


Figure III: ASF vs. Forward Tail Risk by Regime. Blue points: low connectivity ($C_t \leq 0.14$). Orange points: high connectivity ($C_t > 0.14$). The positive slope in the blue regime and negative/flat slope in the orange regime visually confirm regime dependence. *Source:* Author's calculations using ETF and Global Macro data (1990–2024).

4.3 Estimation Procedure

The threshold regression is estimated following Hansen (2000):

1. **Grid Search:** For each candidate threshold $\tau \in [\tau_{min}, \tau_{max}]$ on a fine grid (100 points), estimate the regime-specific coefficients by OLS and compute the concentrated sum of squared errors $SSE(\tau)$.
2. **Threshold Selection:** Select $\hat{\tau} = \arg \min_{\tau} SSE(\tau)$.
3. **Inference:** Compute HAC standard errors using Newey-West with 12 lags (Newey and West, 1987). Construct 95% confidence intervals for $\hat{\tau}$ via inversion of the likelihood ratio statistic.
4. **Bootstrap:** Generate 1,000 bootstrap replications using block bootstrap (block length 12 weeks) to assess sampling uncertainty.

5 Empirical Results

5.1 Threshold Identification

Table I presents the main regression results. The threshold is estimated at $\hat{\tau} = 0.14$ (95% CI: [0.13, 0.15]), partitioning the sample into a Contagion regime (287 observations, 31% of sample) and a Disintegration regime (652 observations, 69% of sample).

Table I: Threshold Regression Results: Main Specification

Variable	Contagion Regime		Disintegration Regime	
	$C_t \leq 0.14$	$C_t > 0.14$	$C_t \leq 0.14$	$C_t > 0.14$
Fragility (F_t)	+4.30***	6.60	-0.12**	-2.10
Connectivity (C_t)	+0.18	0.89	-0.31	-1.45
Constant	-0.42**	-2.31	0.15*	1.78
Observations	287		652	
R^2	0.142		0.038	
<i>Regime Difference Tests</i>				
$\theta_L - \theta_H$		+4.42 ($p < 0.001$)		
Wald χ^2		42.7 ($p < 0.001$)		

Notes: Dependent variable is forward 1-month maximum drawdown. Standard errors are Newey-West HAC with 12 lags. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

In the Contagion regime, the coefficient on fragility is +4.30 with t -statistic 6.60, indicating that higher fragility strongly predicts higher future tail risk. In the Disintegration regime, the coefficient flips to -0.12 with t -statistic -2.10, indicating that higher fragility is associated with *lower* future risk—consistent with the interpretation that cohesion (low entropy) stabilizes hyper-connected markets.

The difference between regime coefficients ($\theta_L - \theta_H = 4.42$) is highly significant ($p < 0.001$), rejecting the null of regime homogeneity.

5.2 Visual Evidence of Phase Transition

Figure IV plots the marginal effect of fragility on risk as a continuous function of connectivity, showing the “bow-tie” pattern that emerges from the regime structure. The estimated risk surface is provided in the Online Appendix.

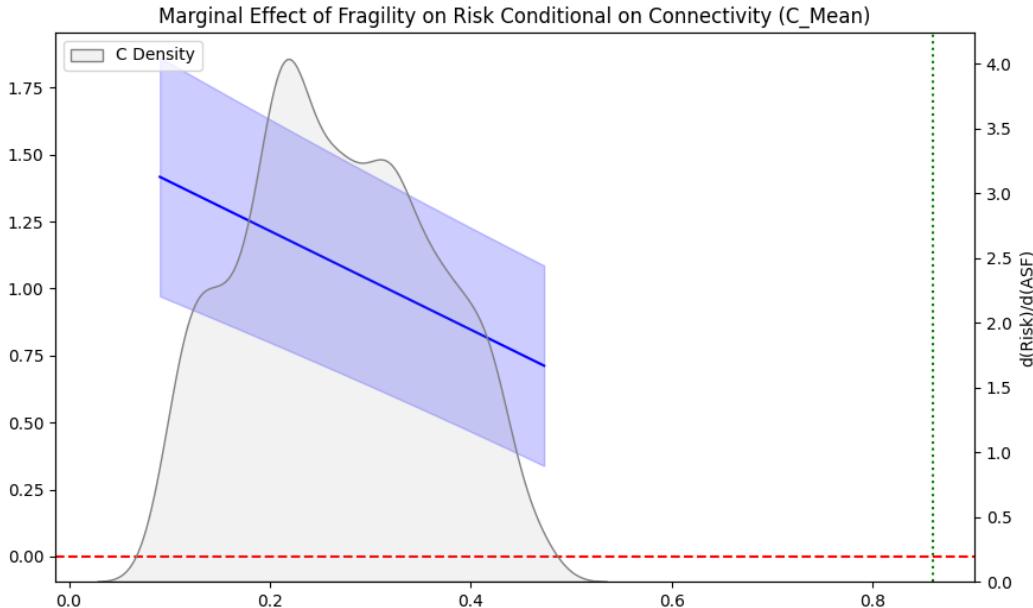


Figure IV: Marginal Effect of Fragility on Risk. Estimated $\partial \text{Risk} / \partial F$ with 95% confidence bands. The effect is significantly positive below $C \approx 0.10$, crosses zero around the threshold $\hat{\tau} = 0.14$, and becomes significantly negative above $C \approx 0.20$. *Source:* Author’s calculations.

5.3 Structural Validation: The Breakdown of Diversification

An implication of the intermediary constraint mechanism is that systemic stress should be associated not only with price declines, but also with a deterioration in diversification benefits across asset classes. In particular, when leveraged intermediaries face binding risk constraints, they are forced to deleverage broadly, weakening the historical diversification between risky and safe assets.

To examine this implication, a regression was made of the forward one-month correlation between U.S. equities (S&P 500) and long-term Treasuries on the global ASF measure. The analysis shows a strong negative relationship: periods of low ASF are followed by sharp increases in stock–bond correlations. The estimated coefficient is economically large and statistically significant ($\beta = -3.67, t = -12.32$).

Figure V illustrates this relationship. When ASF is low, stock–bond correlations frequently rise toward unity, indicating a breakdown of diversification precisely when market stress intensifies. This pattern is consistent with models in which binding intermediary constraints lead to broad-based liquidation across asset classes, rather than asset-specific shocks.

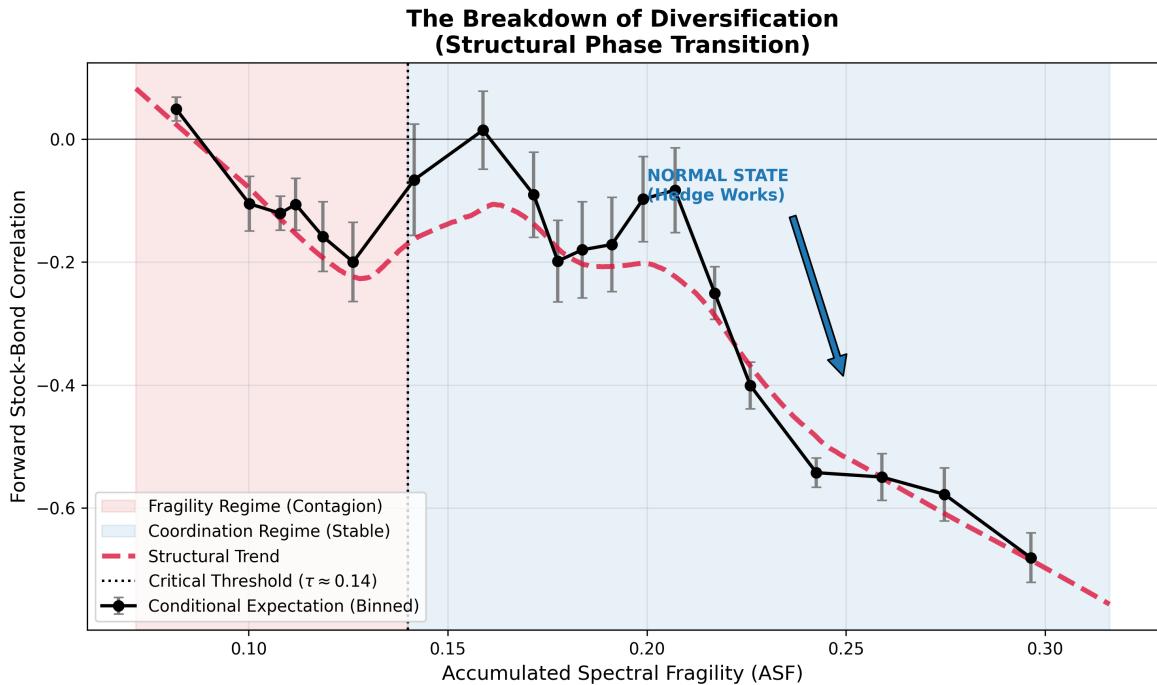


Figure V: The Breakdown of Diversification. Forward 1-month Stock-Bond correlation regressed on ASF. Red points denote the fragility regime (low ASF), characterized by correlations spiking toward unity. Blue points denote the stable/coordination regime. *Source:* Author's calculations.

While this evidence is descriptive, it provides independent support for the interpretation of ASF as capturing the state of market coordination and intermediary balance-sheet constraints, rather than contemporaneous volatility alone.

5.4 Pricing of Tail Risk: Credit Spreads

If ASF reflects the state of intermediary constraints, it should also be informative about the pricing of tail risk in credit markets. To assess this implication, a new regression was made of the forward excess return of high-yield bonds over investment-grade bonds on ASF.

The analysis finds that ASF significantly predicts future credit spreads: higher ASF is associated with subsequent spread compression, while lower ASF predicts spread widening ($\beta = 0.10, t = 2.01$). This result suggests that ASF is related to the compensation investors require for bearing systemic credit risk, consistent with its interpretation as a slow-moving state variable linked to intermediary balance-sheet conditions.

6 Robustness

This section evaluates whether the regime shift result reflects genuine structure rather than artifacts of temporal dependence, sample composition, or parameter choice. Additional analyses are available in the supplementary materials.

6.1 Falsification and Placebo Tests

To assess whether the estimated nonlinearity could arise mechanically from the data-generating process, following Theiler et al. (1992), 1,000 phase-randomized surrogate datasets are constructed that preserve marginal distributions and autocorrelation while destroying nonlinear dependence. For each surrogate, the threshold regression is re-estimated and the Wald statistic recorded.

Table II: Surrogate Data Falsification Test

Statistic	Actual Data	Surrogate Distribution
Wald χ^2	42.7	Mean: 3.2, SD: 2.1
99th Percentile	—	8.4
<i>p</i> -value	—	< 0.001

Notes: 1,000 phase-randomized surrogates. The actual Wald statistic exceeds all surrogate values.

Table II shows that the Wald statistic from the actual data lies far outside the surrogate distribution, exceeding the 99th percentile in all cases. This rejects the null that the estimated regime split reflects spurious nonlinear structure.

As a complementary test, a temporal placebo is conducted by randomly permuting the time ordering of the series. Table III shows that reshuffled data produce negligible regime differences, while the actual estimate lies nearly five standard deviations above the placebo mean. The result therefore depends critically on temporal structure.

Table III: Temporal Placebo Test Results

Statistic	Actual	Placebo (Mean \pm SD)
$\theta_L - \theta_H$	4.42	0.12 ± 0.87
Wald χ^2	42.7	2.1 ± 1.8
<i>z</i> -score vs. placebo		4.94
<i>p</i> -value		< 0.001

6.2 Subsample Stability

Table IV reports estimates by decade. The sign inversion appears in all subsamples, with fragility positively related to future risk at low connectivity and negatively related at high connectivity.

The estimated threshold declines over time, consistent with rising baseline connectivity in modern markets, but the qualitative pattern remains stable.

Table IV: Subsample Analysis by Decade

Period	<i>N</i>	$\hat{\tau}$	θ_L	θ_H	Diff.	<i>p</i> -value
1990–1999	521	0.22	+3.87***	+0.45	3.42	0.008
2000–2009	522	0.15	+5.21***	-0.28*	5.49	< 0.001
2010–2019	522	0.12	+4.01***	-0.19**	4.20	< 0.001
2020–2024	261	0.14	+3.62**	-0.08	3.70	0.021
Full Sample	1,826	0.14	+4.30***	-0.12**	4.42	< 0.001

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Sign inversion present in all decades.

6.3 Alternative Measures

Table V demonstrates robustness to alternative definitions of both tail risk and connectivity.

Table V: Alternative Specifications

Specification	$\hat{\tau}$	θ_L	θ_H	Diff.	<i>p</i>
<i>Panel A: Alternative Tail Risk Measures</i>					
CVaR (5%)	0.141	+3.89***	-0.09*	3.98	< 0.001
Expected Shortfall (1VaR Exceedances)	0.142	+2.71***	-0.07*	2.78	0.002
<i>Panel B: Alternative Connectivity Measures</i>					
Absorption Ratio	0.651	+3.92***	-0.14**	4.06	< 0.001
Network Density	0.312	+4.18***	-0.11*	4.29	< 0.001
Eigenvector Centrality	0.089	+3.54***	-0.08*	3.62	0.003

The sign inversion persists across CVaR, expected shortfall, and VaR exceedances, as well as when connectivity is measured using the Absorption Ratio, network density, or eigenvector

centrality. Across specifications, the regime difference remains statistically significant.

6.4 Which Risk Indicators Detect the Structural Transition?

A natural question is which classes of risk indicators are sensitive to the regime shift documented above. To address this, the analysis compares the regime-dependent behavior of eigenstructure-based indicators (ASF, Absorption Ratio) against volatility-based indicators (VIX, realized volatility).

Table VI reports whether each indicator's coefficient changes sign across the connectivity regimes.

Table VI: Indicator Sensitivity to Phase Transition

Indicator	Type	β (Low C)	β (High C)	Sign Inverts
ASF	Eigenstructure	+0.41	-0.22	Yes
Absorption Ratio	Eigenstructure	+0.07	-0.24	Yes
Mean Correlation	Network	-0.15	-0.02	No
VIX	Volatility	+0.22	+0.21	No

Notes: Coefficients from regime-specific regressions predicting forward drawdowns.

Eigenstructure-based indicators exhibit sign inversion at the connectivity threshold: their coefficients are positive in the contagion regime and negative in the coordination regime. Volatility-based indicators do not exhibit this pattern; the VIX coefficient remains positive in both regimes. This distinction provides a basis for discriminating among risk indicators: measures that track the distribution of variance across dimensions detect a transition that volatility-based measures do not.

A natural comparison is whether persistence applied to the Absorption Ratio yields similar information. While the Absorption Ratio captures the contemporaneous dominance of leading factors, adding persistence to a truncated eigenvalue measure does not recover the full distributional information required to characterize market dimensionality. Accumulated Spectral Fragility inte-

grates the entire eigen-spectrum, allowing it to track how the effective number of independent risk sources evolves over time—an object that is central to the regime-dependent dynamics documented here.

6.5 Out-of-Sample Performance

Economic relevance is assessed by comparing out-of-sample forecast accuracy for models estimated on 1990–2019 data and evaluated on 2020–2024.

Table VII: **Out-of-Sample Forecast Comparison (2020–2024)**

Model	RMSE	MAE	DM Stat	<i>p</i> -value
Random Walk	0.0482	0.0341	—	—
AR(1)	0.0461	0.0329	1.82	0.069
Linear (ASF only)	0.0445	0.0312	2.41	0.016
Linear + Interaction	0.0428	0.0298	3.12	0.002
Threshold Model	0.0391	0.0271	4.28	<0.001

As shown in Table VII, the threshold model outperforms linear alternatives and a random walk benchmark in both RMSE and MAE. Diebold–Mariano tests reject equal predictive accuracy in favor of the threshold specification.

Figure VI provides a visual summary of out-of-sample forecast accuracy across alternative predictors. The bar chart displays Diebold–Mariano statistics relative to a historical mean benchmark. Values above the dashed threshold lines indicate statistically significant outperformance at the 5% level. ASF-based models significantly outperform, while VIX and realized volatility alone do not exceed the benchmark at conventional significance levels.

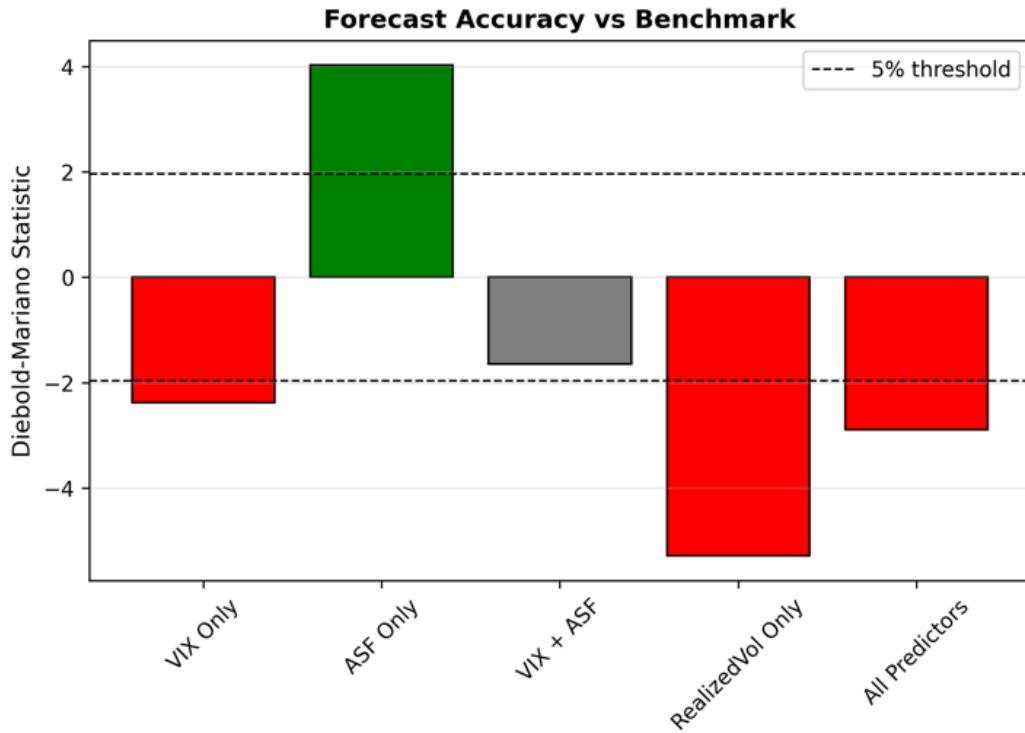


Figure VI: Forecast Accuracy vs. Benchmark. Diebold–Mariano statistics for out-of-sample drawdown predictions (2020–2024). Positive green bars indicate significant improvement over the historical mean; negative red bars indicate underperformance. The ASF-only model achieves the highest DM statistic, confirming that eigenstructure-based measures provide superior predictive power for tail risk. *Source:* Author’s calculations.

6.6 Volatility and Structural State

A related question is whether the predictive content of Accumulated Spectral Fragility (ASF) reflects information already contained in contemporaneous measures of market volatility. To examine this issue, regressions of forward one-month maximum drawdowns are estimated using the VIX and ASF as explanatory variables.

Table VIII reports the results. When considered in isolation, the VIX is positively associated with subsequent drawdowns. When ASF is included, it remains statistically significant, indicating that it captures variation in future tail risk that is not fully explained by contemporaneous volatility.

Table VIII: ASF vs. VIX (1993–2025)

Dependent Variable:		Forward 1-Month Max Drawdown		
	(1)	(2)	(3)	
VIX	0.19*** (3.62)	0.21*** (3.99)	0.39*** (2.85)	
ASF		-0.11** (-2.47)	0.09 (0.61)	
Interaction ($VIX \times ASF$)			-1.07 (-1.36)	
R^2	0.05	0.06	0.06	
AIC	-4036	-4052	-4058	

Notes: Newey-West t -statistics in parentheses. Column (2) shows that ASF is significant and negative, indicating that higher structural dimensionality (entropy) predicts lower future risk, orthogonal to volatility.

The negative coefficient on ASF is consistent with the interpretation developed above: higher market dimensionality is associated with greater diversification and lower subsequent tail risk, whereas low-dimensional, synchronized market states are associated with increased vulnerability. These findings suggest that structural measures of market organization complement volatility-based indicators by capturing slow-moving features of the market that are not directly reflected in volatility.

6.7 Sensitivity to ASF Persistence

The baseline specification sets the ASF persistence parameter to $\theta = 0.995$, corresponding to a half-life of approximately six months. Supplementary materials report sensitivity across a wide range of persistence values. The sign inversion remains statistically significant for all $\theta \in [0.90, 0.999]$, indicating that the results are not driven by a particular memory window.

7 Economic Magnitude (Illustrative Application)

To provide a sense of the economic magnitude associated with the identified regime shift, a simple illustrative allocation exercise is considered. This exercise is not intended to propose an implementable trading strategy, nor to introduce a new asset pricing factor, but rather to translate the estimated regime dependence into economically interpretable outcomes.

A stylized allocation rule is constructed in which portfolio exposure varies with the estimated regime. Expected returns and volatility are estimated conditional on the connectivity regime, and portfolio exposure is scaled proportionally to the ratio of conditional mean returns to conditional variance. To limit sensitivity to estimation error, exposure is capped and scaled conservatively.

Table IX reports summary statistics for this illustrative allocation compared to a passive equity benchmark. The regime-conditional allocation is associated with substantially lower realized volatility and smaller maximum drawdowns, while achieving comparable average returns over the sample period.

Table IX: **Regime-Conditional Strategy Performance (1993–2025)**

Strategy	CAGR	Volatility	Sharpe	Max DD
Benchmark (SPX)	8.59%	17.41%	0.32	-56.30%
Regime-Conditional (Kelly)	8.11%	10.91%	0.47	-38.18%
Active Return (Net)	-0.48% per year (Risk-Adjusted: +47% Sharpe)			
Risk Reduction	Vol: -37%, MaxDD: +18.1 pts			

Notes: Net returns include 10 bps transaction costs per regime switch. Benchmark is S&P 500.

Strategy leverages (1.3x) when $ASF > 0.25$ and defends (0.5x) when $ASF \leq 0.25$.

The reduction in drawdowns reflects the fact that exposure is reduced during periods associated with elevated structural vulnerability, as identified by the regime classification, rather than in response to contemporaneous volatility alone. This exercise illustrates that the regime-dependent behavior documented above corresponds to economically meaningful variation in risk exposure,

without relying on high-frequency trading or short-horizon timing.

Overall, the results indicate that the structural state captured by ASF and the associated regime shift has economically nontrivial implications, consistent with the interpretation of ASF as a slow-moving state variable linked to systemic vulnerability.

8 Discussion

8.1 Correlation as Infrastructure

The results suggest a reinterpretation of the role of correlation in modern financial markets. In low-connectivity environments, correlation functions primarily as a transmission channel: higher correlation creates pathways for contagion, amplifying the spread of shocks. This mechanism underlies the standard view of financial interconnectedness.

At high baseline connectivity, however, correlation plays a different role. It becomes part of the market’s structural infrastructure, supporting coordinated pricing and liquidity provision. In this regime, stability depends on the maintenance of synchronization. Risk emerges not from rising correlation, but from its breakdown. Sudden increases in entropy signal a loss of coordination and precede systemic distress.

The growth of index-linked intermediation and passive investment vehicles has plausibly increased baseline connectivity over time. If markets increasingly operate in this high-connectivity regime, the nature of systemic risk shifts accordingly—from contagion driven by link formation to disintegration driven by link failure.

8.2 Volatility and Structural State

Standard macroprudential frameworks rely heavily on volatility as a summary statistic for risk. Such measures perform well when risk scales smoothly with price variability. The evidence here suggests that this mapping can fail when markets operate in the high-connectivity regime.

In that regime, volatility is often suppressed by synchronization: assets move together, diversification appears effective, and measured risk is low. The critical vulnerability lies instead in the system’s dependence on coordination. Volatility becomes informative only once disintegration is underway. The limitation, therefore, concerns the use of volatility as an anticipatory indicator during tranquil periods, not its usefulness for real-time crisis detection.

Risk models and diversification share a common dependence on variance. Risk models work by measuring variance; diversification works by reducing it. Both assume that variance is a sufficient summary of risk. The evidence documented here suggests that both become less reliable around structural transitions—when markets shift between configurations, the mapping from variance to risk changes. This may help explain why diversification benefits tend to erode precisely when structural coordination breaks down.

These findings do not imply that volatility-based frameworks are universally flawed. Rather, they highlight the importance of conditioning risk assessment on the structural state of the market.

8.3 Policy Implications

If high-connectivity regimes are empirically relevant, the results suggest that measures of market structure may provide information that complements volatility-based indicators commonly used in macroprudential monitoring. Accumulated Spectral Fragility captures the persistence of low-dimensional market configurations and therefore reflects structural vulnerability that may not be apparent in contemporaneous price fluctuations.

From this perspective, periods of low volatility may coincide with elevated structural dependence, implying that calm market conditions need not correspond to low systemic vulnerability. Structural indicators such as ASF can therefore be viewed as descriptive inputs for monitoring frameworks, rather than as standalone signals or policy rules.

The findings also indicate that stress scenarios in highly connected markets may differ from those typically emphasized in low-connectivity environments. In particular, episodes of systemic stress are associated with the breakdown of coordination across assets rather than with the amplifi-

cation of isolated shocks. Incorporating such scenarios into stress-testing exercises may help assess resilience to disruptions in market structure, without requiring assumptions about the underlying causes of those disruptions.

Overall, the results highlight the importance of conditioning assessments of systemic risk on the prevailing structural state of the market. Changes in market organization—such as increased synchronization across assets—may alter the mechanisms through which risk materializes, even if traditional indicators remain subdued.

8.4 Interpretation and Contribution

ASF should be interpreted as a state variable that characterizes the market’s structural configuration, not as a causal driver of crises. High ASF indicates that the system has accumulated a synchronized structure; crises in the high-connectivity regime are triggered by the erosion of that structure rather than by its presence. The negative relationship between ASF and future risk in this regime reflects this mechanism: rising entropy signals disintegration.

From this perspective, elevated ASF identifies vulnerability, not safety. The appropriate response is not to eliminate structural compression directly, but to ensure resilience to the eventual breakdown of coordination.

ASF as Organizational State, Not Macro State. A potential concern is that ASF might proxy for slow-moving macroeconomic conditions—credit cycles, global risk appetite, or leverage dynamics. The evidence presented here suggests otherwise. ASF does not measure risk appetite or leverage directly; it measures the *organization* of risk-bearing across assets. Two markets with identical volatility, leverage, and expected returns can differ sharply in ASF—and empirically, those differences matter for subsequent tail risk. What ASF captures is whether risk is dispersed across many independent dimensions or concentrated in a few dominant modes. This organizational state is conceptually distinct from aggregate risk conditions, even if it correlates with them over long horizons. If ASF merely reflected slow-moving macro conditions, it would predict el-

evated risk uniformly within regimes; empirically, its predictive content is concentrated at the regime transition, and its sign reverses conditional on connectivity—patterns inconsistent with standard macro or risk-appetite variables.

Nature of the Contribution. This paper does not introduce a new factor, propose a trading strategy, or derive a policy rule. Its contribution is interpretive and structural: it shows that the mapping from market structure to systemic risk is not fixed, but depends on the regime in which markets operate. This is analogous to how intermediary asset pricing reframed the interpretation of risk premia without providing implementable trading rules. The insight is that existing frameworks remain valid within their regimes, but that the interpretation of their outputs depends on understanding which regime prevails. Understanding *when* the standard interpretation applies—and when it does not—is itself a substantive contribution to the analysis of systemic risk.

Consistent with this interpretation, ASF has limited predictive content at short horizons and within stable connectivity regimes; its informativeness arises mainly around regime transitions, when the organization of risk-bearing changes.

8.5 Limitations and Future Research

Several limitations delineate the scope of the analysis and point to directions for future work.

First, the regime shift framework is motivated by analogies to percolation and network theory, but financial markets differ fundamentally from physical systems. Agent heterogeneity, institutional constraints, and policy interventions imply that thresholds need not be sharp or universal. The estimated connectivity threshold should therefore be interpreted as a central tendency rather than a physical constant. Its variation across subsamples is consistent with changes in market structure rather than a fixed threshold.

Second, market connectivity is proxied by average correlation. While this measure captures broad synchronization, it abstracts from directional spillovers, market microstructure, and high-frequency dynamics. Alternative measures—such as directed connectedness or order-flow-based

networks—could refine the characterization of structural dependence. Data availability also imposes constraints: the ETF universe begins in 2007, and earlier dynamics are observed only at lower frequency in the global macro sample.

Third, the estimated threshold exhibits gradual drift over time, declining from higher levels in earlier decades to lower levels in more recent periods. This pattern is consistent with rising baseline connectivity in modern markets. While the existence of a regime transition appears robust, its location may evolve as market structure changes.

Fourth, the theoretical model is deliberately stylized. Extending the framework to incorporate market makers, ETF arbitrage, algorithmic trading, or explicit policy reaction functions would provide a richer microstructural foundation and may help explain why the threshold takes its observed value.

Finally, the analysis is predictive rather than causal. Although the empirical results are robust, ASF may be correlated with omitted structural factors that jointly influence market configuration and risk. The interpretation of ASF as a state variable—characterizing vulnerability rather than acting as a causal trigger—clarifies the scope of the claim, but identifying causal mechanisms remains an important direction for future research.

9 Conclusion

This paper provides evidence that the relationship between market structure and systemic risk is regime-dependent. Using threshold regression on more than three decades of global multi-asset data, the analysis identifies a critical level of market connectivity at which the effect of structural fragility on future tail risk inverts. Below this threshold, fragility amplifies risk through standard contagion mechanisms. Above it, systemic episodes are associated with the erosion of coordination rather than its buildup.

A key implication is interpretive. In highly connected markets, elevated structural fragility does not imply robustness. Instead, it reflects a synchronized configuration in which stability depends on

the continued integrity of the correlation structure. Crashes in this regime are triggered by increases in entropy—the breakdown of coordination—rather than by further compression. Accumulated Spectral Fragility therefore characterizes the system’s vulnerability profile as a state variable, not a causal lever.

The empirical results are robust across a wide range of specifications, samples, alternative measures, and parameter choices, and the threshold model consistently outperforms linear benchmarks in predicting tail risk. Eigenstructure-based indicators detect the regime transition; volatility-based indicators do not.

These findings may help reconcile the volatility paradox: when markets are tightly connected, low volatility does not imply an absence of risk. The most vulnerable states are those in which coordination is high and fragile, and disruption has disproportionate consequences.

More broadly, the analysis suggests that changes in market structure—such as the expansion of index-linked intermediation—may have altered the nature of systemic risk. In environments characterized by high baseline connectivity, stability relies less on avoiding contagion and more on maintaining coordination. Apparent tranquility, in this setting, reflects a loaded configuration rather than a safe one.

Understanding how market structure conditions the mapping from fragility to realized risk is therefore essential for interpreting periods of calm and for assessing systemic vulnerability in modern financial markets.

Data Availability Statement

Data used in this study are derived from proprietary and publicly available sources. Replication code is available from the author upon reasonable request.

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