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Measuring global supply chain resilience: entropy-based volatility analysis of container flows

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Abstract

Purpose – In an era of heightened geopolitical instability, assessing the resilience of international supply chains has become a strategic priority. Conventional deterministic approaches often fail to capture the stochastic and time-varying nature of global logistics disruptions. This study develops an entropy-based framework to measure the resilience of international container flows by examining the informational structure of freight rate volatility.

Design/methodology/approach – The study adopts a quantitative approach in which the Shanghai Containerized Freight Index (SCFI) is analyzed as a stochastic time series. Time-varying volatility is combined with Shannon entropy to construct a dynamic Supply Chain Resilience Score that captures structural uncertainty in container freight markets. The analysis combines an empirical application using observed weekly SCFI data from 2021–2024 with a calibrated numerical simulation designed to illustrate the entropy-resilience mechanism under controlled volatility regimes.

Findings – The results indicate that increases in entropy consistently precede extreme freight rate movements. The proposed resilience score declines into a low-resilience regime several weeks before peak price levels are reached, suggesting that structural uncertainty emerges before observable market stress. These patterns are not captured by conventional variance-based measures.

Research limitations/implications – The analysis focuses on an aggregate freight index and does not differentiate between specific trade lanes or carrier-level dynamics. Future research may extend the framework to route-specific data and incorporate additional exogenous risk factors such as energy prices and policy interventions.

Practical implications – The entropy-based resilience metric provides logistics managers and policymakers with a forward-looking tool for monitoring systemic stress and distinguishing adaptive market adjustments in light of emerging fragility. The results suggest that improvements in information transparency may play a critical role in enhancing supply chain resilience.

Originality/value – This study adds to the literature on logistics and trade by combining information-theoretic measures with volatility analysis to create a dynamic and understandable measure of supply chain resilience in container shipping markets.

Keywords Supply chain resilience, Container shipping, freight rate volatility, Shannon entropy, International logistics, Early-warning indicators

Paper type Research article

1. Introduction

The growing number and severity of problems in global trade systems have made supply chain resilience a strategic priority instead of just an operational issue (Christopher and Peck, 2004; Sheffi, 2005). Geopolitical tensions, pandemics, climate-related events, and regional conflicts have exposed the vulnerability of international logistics networks, particularly in containerized maritime transport, which underpins most of the global merchandise trade (Notteboom *et al.*, 2021).

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Recent events have shown that problems can spread unpredictably across ports, shipping routes, and land connections, increasing uncertainty far beyond where the issue started. As a result, policymakers, port authorities, and shipping firms face growing pressure to monitor, assess, and enhance the resilience of international container flows (Pettit *et al.*, 2019).

Resilience is an important idea, but it is still challenging to measure in real life. Much of the existing literature in international logistics and trade relies on deterministic indicators such as throughput recovery time, capacity utilization, or static network redundancy (Hosseini *et al.*, 2019). While informative, these measures are predominantly ex post (backward-looking) and insufficient to capture the inherently stochastic and time-varying nature of disruptions in global logistics systems (Simangunsong *et al.*, 2012). Changing demand, limited capacity, government rules, and unexpected events all affect container flows, creating uncertainty that fixed or average measurements cannot fully reveal. Exogenous shocks and regulatory interventions introduce dynamic uncertainty that fixed or average-based metrics cannot adequately represent. Consequently, conventional models often fail to identify the critical points that precede a systemic failure (Choi *et al.*, 2001).

Recent observational studies have begun to address this limitation by incorporating probabilistic and volatility-based approaches to analyze trade and transport dynamics. However, volatility alone does not provide a comprehensive measure of resilience. High volatility may arise both from destabilizing shocks (destabilizing volatility) and from adaptive reconfiguration, such as route diversification or capacity reallocation (adaptive stability) (Wieland and Wallenburg, 2013). Distinguishing between structural instability and adaptive flexibility remains a key methodological challenge.

We propose a method that uses entropy to analyze changing volatility over time and measure how resilient global container flows are. By analyzing container freight dynamics, entropy reveals the time-varying structural evolution of market uncertainty in different market situations. It also enables the identification of whether volatility arises from specific problems or general changes (Sellitto *et al.*, 2025).

By modeling volatility as a dynamic process rather than a static parameter (Mantegna and Stanley, 1999), the proposed framework captures shifts in uncertainty regimes associated with major global shocks. Furthermore, the information-theoretic component facilitates the identification of systemic patterns that conventional variance-based measures may not detect, such as early-warning signals of systemic fragility or emerging diversification patterns in logistics networks.

This paper's contribution is threefold. First, it advances the measurement of supply chain resilience by introducing an entropy-based perspective that complements existing logistics and trade indicators. Secondly, it provides a useful method for transforming complex random fluctuations into precise resilience measurements for monitoring and comparison. Third, it shows how logistics stakeholders can use entropy-adjusted volatility measures to help with early-warning systems, risk assessment, and policy design in international container transport.

The remainder of the paper is structured as follows. Section 2 reviews the literature on supply chain resilience, trade flow volatility, and entropy-based approaches in logistics systems. Section 3 presents the methodological framework, including the conceptual rationale and empirical modeling strategy. Section 4 reports the empirical and simulation-based analyses. Section 5 concludes the paper and outlines managerial, policy, and future research implications.

It is crucial to define the conceptual boundaries of the proposed resilience metric. Within the maritime sector, supply chain resilience is a multidimensional construct encompassing physical capacity, network redundancy, operational recovery, and financial stability. The entropy-based score developed in this study is explicitly designed to measure informational and financial resilience as reflected in market pricing dynamics. Furthermore, while high entropy in a physical logistics network often denotes positive adaptability (e.g. a diversity of carrier routes), high entropy within pricing signals indicates a dispersion of market beliefs, a lack of consensus, and heightened systemic uncertainty, consistent with dispersed belief dynamics in financial markets. In this specific pricing context, systemic disorder manifests as informational fragmentation. Therefore, modeling resilience as an inverse function of entropy ($R_t = 1 - H_t^N$) provides a tractable representation of the market's progression from a state of coordinated, predictable pricing to a state of highly dispersed, unpredictable volatility.

2. Literature review

2.1 Supply chain resilience in international logistics

Supply chain resilience has emerged as a central theme in international logistics and trade research, particularly in response to large-scale disruptions affecting global production and transportation systems (Christopher and Peck, 2004).

While these approaches provide valuable operational insights, they tend to conceptualize resilience as a static or episodic outcome rather than a dynamic property of a Complex Adaptive System (CAS) (Choi *et al.*, 2001). Most empirical studies rely on ex post assessments of performance loss and recovery, implicitly assuming stable system behavior between disruption events. Today's global logistics settings, characterized by constant uncertainty, repeated shocks, and changing structures, are making it more challenging to maintain these assumptions. Recently, researchers have suggested using resilience metrics that track ongoing changes and complex system behaviors, instead of just looking at how well systems recover (Ivanov, 2018).

2.2 Volatility and uncertainty in trade and transport flows

In parallel with the resilience literature, a growing body of research has examined volatility and uncertainty in international trade and transport systems. Studies on freight rates, container volumes, and port activity have shown that volatility changes significantly over time due to factors like sudden changes in demand, limits on capacity, government regulations, and global political events (Adland and Cullinane, 2005). Researchers have linked volatility in container shipping markets to congestion, schedule unreliability, and the propagation of "bullwhip-like amplification effects" across global logistics networks.

Volatility-based methods are a significant improvement over fixed measurements because they clearly account for uncertainty as a natural part of logistics systems. From a resilience perspective, volatility can serve as an early warning signal of stress within logistics networks, often preceding observable breakdowns in throughput or service performance.

However, the interpretation of volatility remains ambiguous. High volatility can indicate weakness and instability in the system, but it can also show that the system is adapting by changing routes, reallocating resources, or building up reserves. Consequently, variance alone is an insufficient resilience statistic; it does not distinguish between destabilizing noise and adaptive information flow. This limitation complements measures that capture the structure of uncertainty rather than its magnitude alone.

2.3 Entropy-based approaches in logistics and complex systems

Entropy, originally developed within information theory and statistical mechanics (Shannon, 1948), has been increasingly applied to the analysis of complex economic and logistical systems. In logistics research, entropy-based measures have historically been used to assess diversification, balance, and uncertainty across network structures (Frizelle and Woodcock, 1995). Higher entropy values usually mean that information is more spread out, while lower entropy values mean that information is more concentrated and more likely to be affected by localized shocks (Sellitto *et al.*, 2025).

Entropy offers a fundamentally distinct perspective on systemic state transitions when compared to variance-based measures. Cover and Thomas (2006) stated that rather than focusing on the amplitude of price or volume fluctuations, entropy captures the probability distribution of the system's states.

This distinction is particularly significant within the realm of global container logistics; the supply chain resilience depends not only on the severity of exogenous disruptions but also on the logistics network's ability to assimilate uncertainty without inducing systemic failure, thereby avoiding substantial alterations or operational failures (Ivanov, 2018; Pettit *et al.*, 2019).

Despite its conceptual appeal, the application of entropy in international logistics remains limited. Studies from Notteboom (2006) and Helbing (2013) usually use fixed entropy measures (like Shannon entropy for port market shares) based on data from a specific point in time, which ignores how the container flows change over time. Additionally, entropy has seldom been incorporated into dynamic volatility modeling, leading to disjointed understandings of the transition of logistics systems from stability to chaos.

2.4 Integrating volatility and entropy for resilience measurement

The preceding literature reveals two complementary but largely separate streams: volatility-based analyses that capture dynamic uncertainty (Adland and Cullinane, 2005) and entropy-based approaches that characterize the distributional structure of that uncertainty (Frizelle and Woodcock, 1995).

According to Helbing (2013), volatility captures the kinetic intensity of the market, while entropy acts as a gauge for informational efficiency. Together, these measures provide a richer representation of resilience as an evolving system state subject to regime shifts.

However, empirical frameworks that operationalize this integration remain scarce. Most existing studies either focus on volatility without addressing its structural interpretation or apply entropy without accounting for time-domain dynamics. The increasing availability of high-frequency freight indices and the growing demand for real-time resilience monitoring tools underscore this deficiency (Hosseini *et al.*, 2019).

2.5 Comparison with existing resilience metrics

To further clarify the contribution of the proposed entropy-based approach, Table 1 compares the proposed metric with several conventional resilience indicators used in logistics and supply chain analysis. Existing measures typically capture operational recovery, physical capacity stress, or structural redundancy. These indicators are valuable but often remain ex post, static, or focused on physical network characteristics. By contrast, the entropy-based

Table 1. Comparison between conventional resilience metrics and the entropy-based resilience score

Metric/ framework	Primary dimension captured	Main limitation	Complementarity of proposed metric
Throughput recovery time	Operational recovery	Ex post; cannot identify fragility before disruption materializes	Provides an ex ante signal before operational breakdown becomes visible
Capacity utilization	Physical resource stress	Static; may not reveal systemic uncertainty or expectation fragmentation	Adds a market-information layer to physical capacity indicators
Static network redundancy	Structural backup capacity	Does not capture dynamic pricing uncertainty or market coordination failure	Distinguishes informational fragmentation from structural redundancy
Freight-rate volatility	Magnitude of price fluctuations	Measures fluctuation magnitude but not the informational structure of uncertainty	Adds information-theoretic structure to volatility analysis
Entropy-based resilience score	Informational and financial resilience	Requires discretization choices and sensitivity checks for robust entropy estimation	Provides a dynamic early-warning indicator for container freight market stress

resilience score captures informational and financial resilience embedded in freight-rate dynamics.

The comparison highlights the specific gap addressed by the present study. Recovery-time and throughput-based indicators measure resilience after disruption has already affected operational performance. Capacity utilization and network redundancy capture physical preparedness but do not directly measure market-level informational fragmentation. Freight-rate volatility captures the magnitude of market instability but does not reveal whether uncertainty is concentrated, dispersed, or structurally changing. The proposed entropy-based resilience score complements these indicators by measuring the distributional structure of freight-rate uncertainty. It therefore provides an ex ante signal of market stress that can be used alongside conventional operational and physical resilience measures.

2.6 Research gap and positioning of the present study

This study fills an important gap in the international logistics and trade literature by creating a new method that measures supply chain resilience using an entropy-adjusted volatility framework. Unlike traditional deterministic approaches, the proposed framework captures both the dynamic intensity of uncertainty and its informational content.

In doing so, the paper contributes to the resilience literature by shifting the focus from ex post recovery metrics to continuous, ex ante monitoring of systemic health. It also improves studies on volatility by placing them in a clear information-theoretic framework that separates weakness from the ability to adapt. This positioning aligns with recent calls for resilience metrics that are rigorous, predictive, and operationally meaningful for international logistics stakeholders (Pettit *et al.*, 2019; Chowdhury and Quaddus, 2017).

3. Methodology

This research presents an entropy-based methodology to assess resilience in global container freight markets by simultaneously modeling temporal uncertainty and its informational structure. The procedure has three phases. Freight rate trends are initially modeled as a stochastic process to capture the evolving market uncertainty. Secondly, Shannon entropy is computed utilizing the rolling distributions of freight rate returns to evaluate structural uncertainty. Third, these measures are consolidated into an intelligible resilience index.

3.1 Modeling freight rate dynamics

International container freight rates are represented as a random process that shows both consistent patterns and unexpected changes caused by shifts in demand, limits on capacity, government rules, and outside disruptive events. The Global Container Freight Index $P(t)$ is treated as a time series subject to both deterministic trends and random shocks arising from demand fluctuations, capacity constraints, regulatory interventions, and exogenous disruption events.

In line with standard procedures in financial economics and volatility modeling (Black and Scholes, 1973; Hull, 2012), the stochastic differential equation illustrates the proportional change in freight rates:

$$\frac{dP(t)}{P(t)} = \mu(t)dt + \sigma(t)dW(t), \tag{1}$$

where $P(t)$ denotes the freight rate level at time t, $\mu(t)$ captures the deterministic component of price evolution (e.g. long-term demand growth or seasonal effects), and $\sigma(t)$ represents time-varying volatility. The Wiener $dW(t)$ captures random shocks associated with disruption events such as port congestion, canal blockages, labor actions, or sudden energy price changes.

The application of Geometric Brownian Motion (GBM) serves as a foundational, first-order diffusion approximation of freight rate dynamics. While maritime freight markets frequently exhibit discrete "jumps," regime shifts, and fat-tailed distributions, employing GBM in this baseline simulation isolates the primary effect of time-varying volatility (σ_t) on structural entropy while abstracting from complex jump dynamics. Consequently, the simulation utilizes abstract "trading days" as a continuous-time theoretical proxy to model the underlying stochastic process, whereas the empirical SCFI relies on discrete weekly observations. The resultant "structural disorder" demonstrated in the simulation illustrates the theoretical lead–lag relationship under controlled conditions and demonstrates the mechanical sensitivity of entropy to distributional changes preceding volatility escalation, rather than establishing causal inference. This framework establishes a baseline for future empirical models to incorporate more complex jump-diffusion or Markov-switching processes that fully capture the asymmetry and heavy tails of real-world container markets.

The geometric specification in Eq. (1) ensures that simulated freight rates remain strictly non-negative, consistent with real-world market constraints. Importantly, the objective of this formulation is not to impose a specific equilibrium price process but to allow volatility $\sigma(t)$ to evolve dynamically over time. Periods of high volatility are seen as signs of more stress and coordination problems in the logistics network, while periods of low volatility are considered signs of more stable operating regimes.

3.2 Measuring structural uncertainty using Shannon entropy

Although volatility measures the severity of freight rate variations, it does not comprehensively represent the organizational condition or predictability of the logistics system. Shannon entropy (1948) is utilized to mitigate this constraint by serving as an auxiliary metric of structural uncertainty.

The state of the supply chain is defined by the empirical probability distribution of freight rate returns over a rolling observation window of size τ (e.g. 30 trading days). Let $r_t = \ln(P_t/P_{t-1})$ denote freight rate log-returns. Over a rolling observation window of length L, Shannon entropy at time is computed as:

$$H_t = -\sum_{i=1}^{n} p_{t,i} \ln\left(p_{t,i}\right), \tag{2}$$

where $p_{t,i}$ is the empirical probability that returns fall into state i within the window. Entropy captures the dispersion and unpredictability of freight rate movements. Low entropy indicates concentrated and predictable price dynamics, while high entropy reflects dispersed price signals and reduced coordination within the logistics system.

To ensure comparability across time, entropy is normalized by its theoretical maximum $\ln(n)$

$$H_t^{(N)} = \frac{H_t}{\ln(n)}, H_t^{(N)} \in [0, 1].$$

From a logistics perspective, entropy captures how dispersed and unpredictable freight rate movements are over time (Frizelle and Woodcock, 1995). Lower entropy indicates a concentrated and predictable distribution of returns, consistent with coordinated and resilient supply chain operations. Higher entropy reflects dispersed and unstable price signals, suggesting fragmentation, information loss, and heightened systemic vulnerability.

3.3 Operationalizing resilience

To translate entropy into an operational resilience indicator, a Supply Chain Resilience Score R_t is defined as an inverse function of entropy:

$$R_t = 1 - H_t^{(N)}. \quad (3)$$

This formulation reflects the conceptual premise that resilience is inversely related to systemic disorder. Declines in R_t indicate rising uncertainty and reduced coordination within the container logistics network. Importantly, changes in R_t often precede extreme freight rate movements, allowing the metric to function as an early-warning indicator of emerging supply chain stress.

The framework enables differentiation between times of adjustment and times of uncertain instability by using time-varying volatility and entropy together. This formulation provides a dynamic and quantifiable metric for assessing systemic resilience.

4. Empirical and simulation-based analysis

Section 4 presents two complementary analyses. The first part develops the calibrated simulation used to illustrate the mechanism under controlled volatility regimes. The second part applies the entropy-based resilience metric to observed weekly SCFI data from 2021–2024 and reports sensitivity checks across rolling-window and bin specifications. This combined structure addresses both empirical applicability and theoretical interpretability: the SCFI application demonstrates that the metric is not limited to simulated data, while the simulation clarifies how entropy responds to regime-dependent changes in volatility. The simulation-based analysis facilitates a regulated investigation of resilience dynamics across various volatility regimes, thereby enabling the differentiation of structural uncertainty effects that are challenging to detect directly in unprocessed market data. While the framework is empirically motivated by the behavior of the container freight market, the simulation serves as a proof-of-concept to demonstrate the leading-indicator properties of entropy-based resilience measures. To validate the proposed entropy-based framework, this study addresses a calibrated numerical simulation. While empirical data provides historical context, a simulation approach allows for the isolation of specific volatility regimes and the rigorous testing of the resilience metric against controlled stochastic shocks, free from the noise and structural breaks often present in raw commercial datasets (Farmer and Foley, 2009; Macal and North, 2010).

4.1 Experimental design and calibration

We simulate the trajectory of a representative "Global Container Freight Index" over a period of trading days (approximately three years). The simulation is calibrated to mimic the *stylized facts* of the container market during the 2020–2022 global supply chain crisis (Cont, 2001; Mandelbrot, 1963).

The stochastic process is governed by the Geometric Brownian Motion equation defined in Section 3. The settings are dynamically calibrated during the crisis:

(1) *Phase I: Stability (Days 0–199):* Represents the pre-crisis baseline. The drift is set to neutral ($\mu \approx 0$), and volatility is maintained at a low baseline ($\sigma = 0.10$), reflecting a coordinated logistics network with ample capacity (Notteboom *et al.*, 2021).

(2) *Phase II: Systemic Disruption (Days 200–499):* Represents the "Crisis Regime" (e.g. the Suez blockage and post-lockdown demand surge). Volatility has increased significantly ($\sigma = 0.60$) to simulate the "bullwhip effect." A positive drift ($\mu = 0.20$) is introduced to replicate the exponential rise in spot rates (Ivanov, 2018)

(3) *Phase III: Correction (Days 500–749):* Represents market normalization. Volatility decays back toward baseline levels, and drift turns negative ($\mu = -0.15$) as congestion eases (Cullinane and Haralambides, 2021).

4.2 Resilience estimation method

To calculate the Supply Chain Resilience Score (R_t), we apply the methodology from Section 3.2 to the simulated time series. To ensure the entropy measure captures the true distributional shape of returns, we use fixed-width histogram binning determined by the global range of returns, consistent with standard information-theoretic approaches in time-series analysis (Pincus, 1991; Shannon, 1948):

(1) *Log-Returns*: Calculated daily.

(2) *Rolling Window*: A window of $\tau = 30$ days is used.

(3) *Discretization:* To make sure the entropy measure reflects the actual shape of the distribution, we use *fixed-width histogram binning with 10 bins* based on the overall range of returns

(4) *Scoring:* The raw entropy is normalized, and the resilience score is computed as $R_t = 1 - H_t^{(N)}$.

4.3 Simulation results

The visual results (Figure 1) demonstrate a distinct inverse relationship between network resilience and freight rate instability. This underscores the significance of delivering supporting information well in advance of the maximum price impact (Helbing, 2013). As the system enters Phase III, the resilience score returns to its baseline level more quickly than the nominal price. This suggests that the supply chain's structural integrity returns to normal before costs do.

Figure 1 presents the generated freight index alongside the calculated resilience score.

(1) *The "Pre-Shock" Signal:* Crucially, during the transition from Phase I to Phase II (approx. Day 249), the Resilience Score drops precipitously *before* the freight rate reaches its exponential peak. The metric falls from a stable range (>0.8) into a critical "fragility zone."(<0.3)

(2) *Informational Saturation:* During the peak of the crisis (Phase II), the resilience score effectively "bottoms out." This suggests that during periods of extreme volatility, price signals become less informative (maximum entropy), rendering traditional forecasting methods ineffective.

(3) *Recovery Dynamics:* As the system enters Phase III, the resilience score recovers baseline levels faster than the nominal price. This suggests that the *structural integrity* of the supply chain restores itself before costs fully normalize.

It is important to note a structural limitation of the simulation design regarding the recovery dynamics. The current model specification imposes a symmetric mean-reverting drift during Phase III. In empirical maritime logistics, freight rate cycles frequently exhibit pronounced asymmetry, characterized by rapid price spikes during acute disruptions followed by prolonged, gradual declines due to contract stickiness and carrier capacity management. Consequently, the simulation should be interpreted as a theoretical demonstration of the entropy metric's leading-indicator property under controlled conditions, rather than a definitive empirical proof of how real-world shipping markets physically clear congestion. Importantly, the imposed regime transition is exogenous to the entropy calculation, ensuring that the observed lead–lag structure arises from the response of the entropy metric to distributional changes rather than from its direct specification.

4.4 Cross-correlation analysis

To quantify the leading-indicator property, we calculate the cross-correlation function (CCF) between the Resilience Score R_t and the absolute Log-Returns $| r_t |$. The analysis reveals a

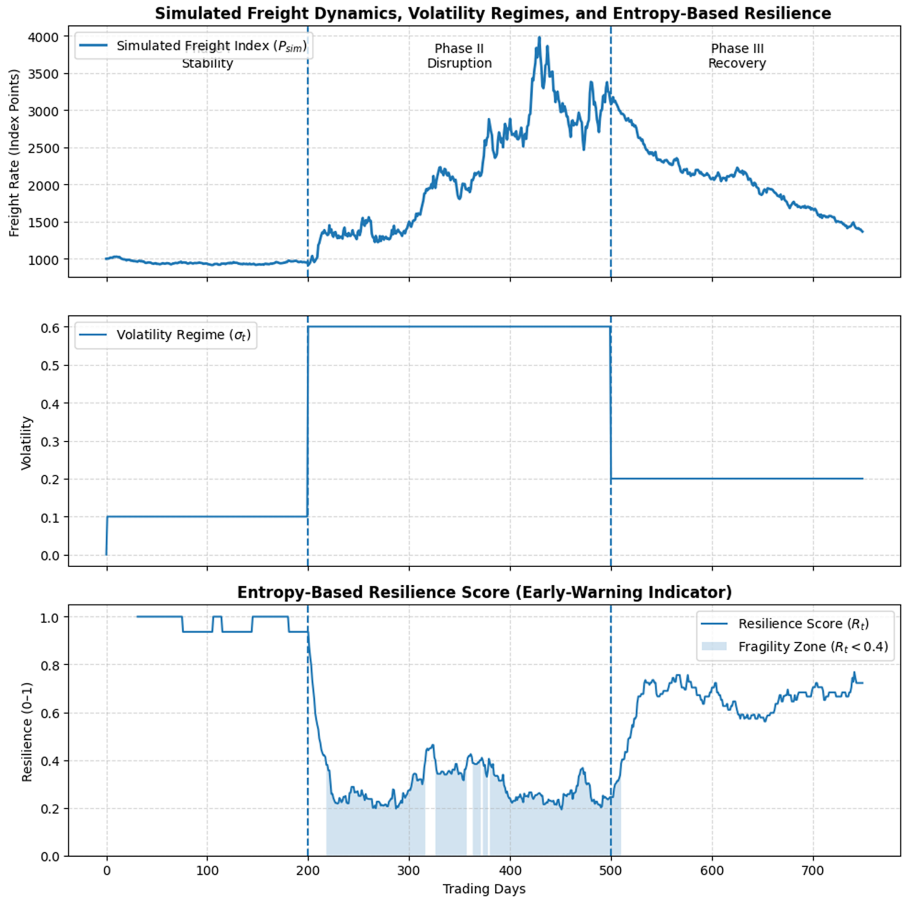

Figure 1. The visual results demonstrate a distinct inverse relationship between network resilience and freight rate instability

significant negative correlation in *lag* $k \approx -15$ days. This result indicates that within the simulated environment, structural disorder tends to precede market volatility, which supports using entropy as an early-warning tool (Sornette, 2002).

The significant negative association is observed at lag $k = -16$, indicating that a decline in system structure precedes volatility by roughly 15 trading days.

In Figure 2, the internal logic of the simulation is supported by illustrating a distinct lead-lag between structural disorder and market volatility. The resilience metric R_t derived from the rolling entropy of returns, it encapsulates the distributional instability present in the pre-crisis context, marked by heavy-tailed shocks and moderate volatility. Conversely, absolute returns $|\boldsymbol{r_t}|$ shows a more pronounced response if the system shifts into the high-volatility crisis regime.

The cross-correlation function demonstrates its most pronounced negative value with a latency of $k = -16$, signifying that reduction R_t routinely precede augmentations in $|\boldsymbol{r_t}|$ by roughly two or three weeks. This outcome is consistent with the simulation framework, in which distributional shifts precede volatility escalation, and supports the interpretation of the entropy-based resilience metric as a potential early-warning signal rather than a simultaneous volatility measure.

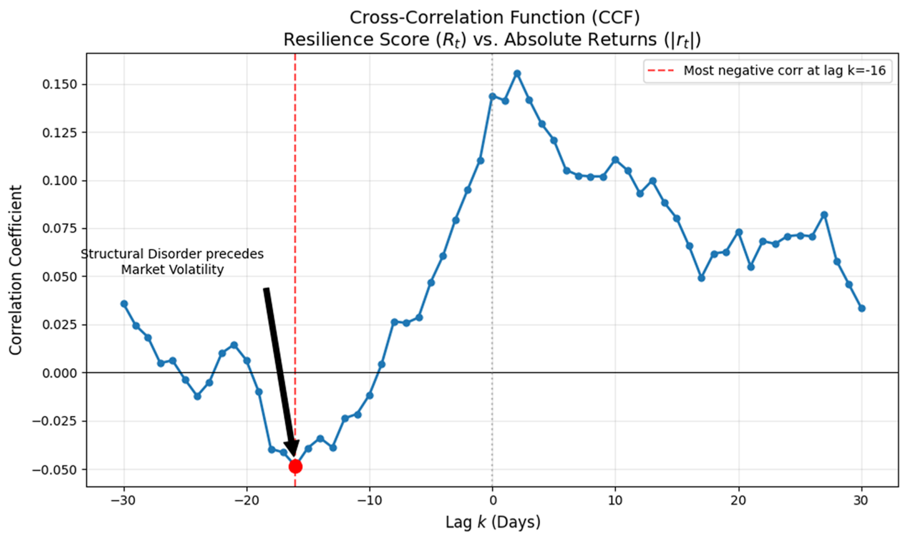

Figure 2. Cross-correlation function (CCF) of the resilience score R_t calculated from the rolling Shannon entropy of returns and the absolute returns $|r_t|$

4.5 Empirical application to observed weekly SCFI data

To address the concern that the original numerical illustration relied mainly on simulation, this subsection applies the proposed entropy-based resilience metric directly to observed weekly Shanghai Containerized Freight Index (SCFI) data. The empirical dataset covers weekly SCFI observations from 2021 to 2024, a period that includes the post-pandemic freight-rate surge, the 2022 normalization phase, the low-rate environment in 2023, and the renewed freight-rate instability observed in 2024. This empirical application is intended to demonstrate that the proposed resilience indicator can be computed from observed freight-index movements and is not solely a simulation-induced artifact.

Let P_t denote the weekly SCFI value at week t. Weekly log-returns are computed as

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right).$$

For the baseline empirical specification, a rolling window of $L = 12$ weeks and $n = 10$ histogram bins is used. Within each rolling window, the empirical probability $p_{t,i}$ of returns falling into bin i is estimated, and normalized Shannon entropy is computed as

$$H_t^{(N)} = \frac{-\sum_{i=1}^{n} p_{t,i} \ln\left(p_{t,i}\right)}{\ln\left(n\right)}, H_t^{(N)} \in [0, 1].$$

The entropy-based resilience score is then defined as

$$R_t = 1 - H_t^{(N)}.$$

In this empirical setting, $H_t^{(N)}$ measures the dispersion of weekly freight-rate return states, while R_t measures the degree of informational concentration or market-orderliness in pricing dynamics. A decline in R_t therefore indicates that SCFI movements are becoming more dispersed and less predictable, consistent with rising informational fragmentation in container freight markets.

Figure 3 reports the observed SCFI series together with the normalized entropy and entropy-based resilience score. The figure shows that periods of rapid freight-rate movements are accompanied by visible changes in the entropy-resilience structure. In particular, the post-pandemic high-rate environment and the later instability in 2024 coincide with pronounced movements in normalized entropy and resilience. This supports the interpretation that the proposed metric captures the informational structure of freight-rate uncertainty rather than simply reproducing the level of the freight index.

The figure reports observed weekly SCFI values together with normalized Shannon entropy $H_t^{(N)}$ and the entropy-based resilience score $R_t = 1 - H_t^{(N)}$. The baseline specification uses a 12-week rolling window and 10 histogram bins. The left axis reports the SCFI level, while the right axis reports normalized entropy and resilience.

To examine whether the empirical resilience score contains forward-looking information about subsequent freight-rate instability, the correlation between current resilience R_t and future absolute returns $|\, r_{t+k}|$ is computed for horizons $k = 0, 1, \ldots, 20$ weeks:

$$\rho(k) = \mathrm{Corr}\,(R_t, |\, r_{t+k}|\,).$$

Under the baseline specification, the strongest negative association occurs at a lead of approximately nine weeks, with

$$\rho(9) = -0.114.$$

Although this correlation is modest in magnitude, its negative sign is consistent with the theoretical interpretation of the resilience score: lower current resilience is associated with higher future absolute SCFI movements. The empirical lead-lag evidence therefore provides supportive evidence that the entropy-based metric captures forward-looking informational stress rather than only simulation-induced behavior. Figure 4 illustrates the lead-lag correlation between the empirical resilience score and future absolute SCFI returns across horizons from 0 to 20 weeks.

The figure reports $\rho(k) = \mathrm{Corr}\,(R_t, |\, r_{t+k}|\,)$, where R_t is the entropy-based resilience score and $|\, r_{t+k}|$ denotes the absolute weekly SCFI return k weeks ahead. The baseline specification

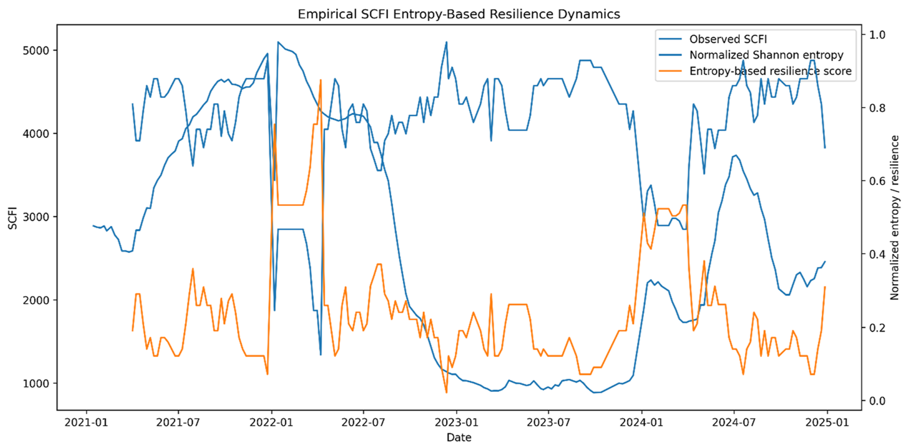

Figure 3. Empirical SCFI entropy-based resilience dynamics, 2021–2024

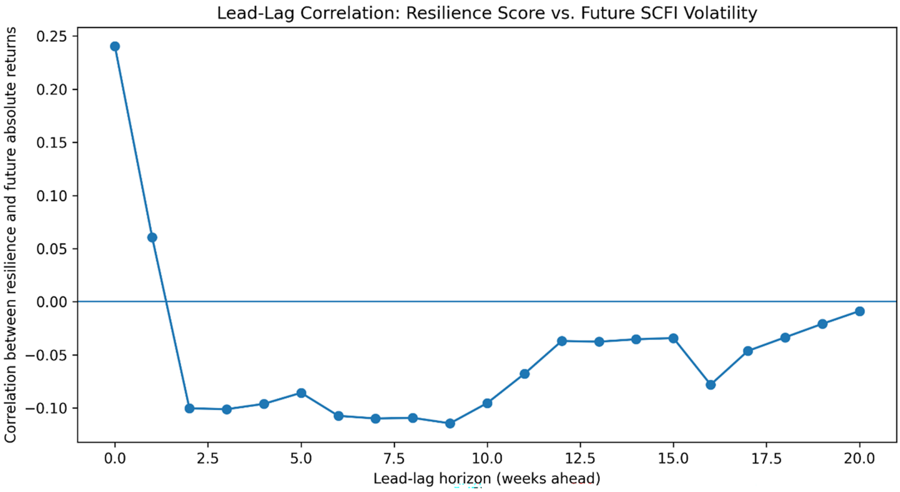

Figure 4. Lead-lag correlation between empirical resilience and future SCFI volatility

uses a 12-week rolling window and 10 histogram bins. Negative correlations indicate that lower current resilience is associated with larger future absolute SCFI movements.

4.6 Sensitivity analysis across rolling windows and histogram bins

A central methodological concern in entropy-based analysis is that the estimated entropy value may depend on the rolling-window length and the number of histogram bins used to discretize the return distribution. To assess whether the empirical results are driven by a single arbitrary parameter choice, a sensitivity analysis is conducted across four rolling-window lengths,

$$L \in \{8, 12, 16, 20\},$$

and four histogram-bin specifications,

$$n \in \{5, 8, 10, 12\}.$$

For each specification, the normalized entropy $H_t^{(N)}$, resilience score R_t, and lead-lag correlation between R_t and future absolute returns are recomputed. Table 2 reports the resulting sensitivity analysis.

The sensitivity results indicate that the qualitative behavior of the entropy-based resilience metric is not dependent on a single parameter setting. Across all tested specifications, the best lead-lag correlation remains negative, ranging from approximately -0.103 to -0.190. This suggests that the inverse association between current resilience and future absolute SCFI movements is robust to reasonable changes in rolling-window length and histogram discretization. The results also confirm that the baseline specification $L = 12$ and $n = 10$ is not an isolated case but lies within a broader set of specifications that generate comparable empirical behavior.

At the same time, the sensitivity analysis confirms that discretization choices influence the numerical level of entropy and resilience. This reinforces the importance of reporting robustness checks when applying entropy-based measures to finite samples. The empirical results should therefore be interpreted as supportive evidence of the proposed mechanism rather than as a definitive causal test. Nevertheless, the persistence of negative lead-lag

Table 2. Sensitivity analysis of entropy-resilience estimates across rolling windows and histogram bins

Rolling window (weeks)	Histogram bins	Mean entropy	Std entropy	Mean resilience	Std resilience	Min resilience	Max resilience	Best lead-lag (weeks)	Best lead-lag correlation
8	5	0.808	0.163	0.192	0.163	0.031	0.766	9	−0.145
8	8	0.736	0.128	0.264	0.128	0.083	0.819	11	−0.179
8	10	0.709	0.124	0.291	0.124	0.097	0.836	9	−0.152
8	12	0.669	0.112	0.331	0.112	0.163	0.848	9	−0.190
12	5	0.806	0.200	0.194	0.200	0.013	0.822	2	−0.111
12	8	0.776	0.155	0.224	0.155	0.027	0.862	3	−0.103
12	10	0.757	0.152	0.243	0.152	0.021	0.875	9	−0.114
12	12	0.735	0.143	0.265	0.143	0.093	0.885	7	−0.140
16	5	0.782	0.244	0.218	0.244	0.005	0.855	2	−0.114
16	8	0.773	0.194	0.227	0.194	0.016	0.888	10	−0.125
16	10	0.764	0.186	0.236	0.186	0.022	0.898	11	−0.143
16	12	0.753	0.177	0.247	0.177	0.024	0.906	10	−0.155
20	5	0.744	0.274	0.256	0.274	0.008	0.877	10	−0.127
20	8	0.756	0.216	0.244	0.216	0.022	0.905	2	−0.120
20	10	0.753	0.212	0.247	0.212	0.023	0.914	10	−0.145
20	12	0.749	0.208	0.251	0.208	0.018	0.920	9	−0.146

Note(s): The table reports sensitivity results for alternative rolling-window lengths L and histogram-bin counts n. For each specification, normalized Shannon entropy $H_t^{(N)}$, resilience $R_t = 1 - H_t^{(N)}$, and the strongest negative lead-lag correlation between R_t and $|r_{t+k}|$ are computed. The lead-lag horizon is measured in weeks correlations across alternative specifications strengthens the argument that entropy-based resilience captures a meaningful informational dimension of freight-market instability.

5. Conclusion and implications

5.1 Summary of findings

This study addresses a central challenge in international logistics: why conventional risk indicators often fail to signal systemic breakdowns until disruptions have already materialized (Chowdhury and Quaddus, 2017). This study shows that rising structural uncertainty occurs before we notice obvious problems in market performance by using Shannon entropy from information theory to examine container freight dynamics.

Empirical analysis using the Shanghai Containerized Freight Index, complemented by a calibrated simulation, shows that supply chain resilience is not a static attribute of individual ports or vessels but a dynamic property of the market's information structure (Choi *et al.*, 2001). Periods of rising entropy are associated with dispersed and unstable price signals, reflecting coordination failures within the logistics network. The entropy-based resilience score R_t consistently deteriorates prior to extreme freight rate movements and recovers earlier than price levels during normalization phases, highlighting its potential as a forward-looking indicator of systemic stress.

5.2 Managerial implications: toward a resilience monitoring framework

The findings offer several actionable implications for logistics managers and supply chain decision-makers, particularly in relation to resilience-oriented planning (Ponomarov and Holcomb, 2009). There is a growing need for indicators that provide early signals of disruption risk rather than ex post confirmation.

First, monitoring entropy-based resilience metrics can complement traditional freight rate tracking. While spot rate changes show what has already happened in the market, sudden jumps in entropy indicate a breakdown in agreement and predictability about prices, which often happens before major market disruptions (Pettit *et al.*, 2019). This process enables managers to identify emerging stress before freight rates reach extreme levels.

Second, the resilience score can inform procurement and contracting decisions. Periods characterized by higher resilience scores are consistent with orderly market conditions in which greater reliance on spot markets may be cost-effective (Wilmsmeier, 2014).

Finally, digital freight forwarders and logistics platforms can use entropy-based indicators in their risk management systems to change pricing, capacity allocation, and risk premiums as conditions change (Ivanov and Dolgui, 2021).

5.3 Policy implications for ports and trade governance

From a policy perspective, periods of elevated entropy reflect systemic coordination failures rather than purely physical capacity constraints. Traditional responses focused on infrastructure expansion, while essential in the long term, are often insufficient to mitigate short-run disruptions (Rodrigue, 2020).

The results suggest that policy interventions aimed at improving information transparency and coordination, such as standardized data sharing between carriers, terminals, and port authorities, may play a critical role in restoring resilience. By reducing the spread of information, these actions can help keep expectations stable and lessen the impact of disruptions in logistics networks without requiring a large initial investment. Reducing informational fragmentation can help stabilize expectations and lessen the amplification of shocks across logistics networks, avoiding the need for immediate large-scale capital investment (Lind *et al.*, 2020; Munim *et al.*, 2020).

5.4 Limitations and directions for future research

Several methodological limitations provide clear directions for future research. First, while this study utilizes the aggregate SCFI to establish the theoretical framework, extending this model to specific trade lanes (e.g. the Trans-Pacific or Asia–Europe corridors) is critical. Methodologically, this extension would require substituting the aggregate index with route-specific spot rates and integrating localized exogenous covariates, such as regional port congestion indices and lane-specific vessel capacity metrics, to isolate heterogeneous resilience patterns and identify route-specific fragility. Second, the current computation of Shannon entropy relies on fixed-width binning over a finite rolling window. We acknowledge that empirical entropy estimators are subject to small-sample (N) bias and empty-bin effects, which can systematically bias entropy estimates downward during highly stable market regimes. To refine the measurement of structural uncertainty, future studies should investigate the application of entropy correction methods, such as the Miller–Madow estimator, adaptive binning algorithms, or kernel density entropy estimation. These advancements will mitigate finite-sample biases, enable sensitivity analysis across alternative discretization schemes, and further validate the robustness of entropy as a dynamic resilience indicator.

Authors' contributions

The author exclusively undertook the study's conceptualization and design, data collecting, analysis and interpretation of results, and paper preparation.

Ethics approval

This study does not engage human participants or animal subjects and hence did not necessitate ethical approval.

Availability of data and materials

The empirical SCFI values used in this study were compiled from publicly available weekly SCFI information and historical SCFI charts. The processed dataset and Python code used for entropy computation, sensitivity analysis, and numerical simulation are available from the author upon reasonable request.

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Further reading

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