Rumor Spreading in Economic Networks via Threshold Models: Simulations and Empirical Validation

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Abstract

The propagation of rumors and misinformation through financial markets can amplify volatility and precipitate systemic events. We study rumor spreading using deterministic threshold models on networks that represent channels of influence between economic agents. The paper combines: (i) a concise mathematical formulation of the threshold process, (ii) synthetic experiments on canonical network models (Erdős–Rényi, Barabási–Albert, Watts–Strogatz), and (iii) an empirical validation on a small cross-section of US equities where correlations of returns define the influence network. Results show that network heterogeneity (presence of hubs and clustered communities) substantially increases cascade susceptibility for a wide range of individual thresholds. We discuss implications for monitoring, early-warning, and targeted interventions in financial systems.

1 Introduction

Rumors, misinformation, and herd behavior are long-known drivers of excess volatility and systemic risk in financial markets. The 2008 crisis illustrated how local shocks and cascading confidence losses may propagate through interdependent institutions and asset holdings, inducing broader market dislocations. In modern markets, digital communication channels and rapid dissemination of news amplify the potential for fast, global spread of unverified information. Modeling rules for adoption and spread is therefore crucial for understanding vulnerabilities and designing mitigation strategies.

Network models combined with contagion processes provide a natural language to study these phenomena. In particular, threshold models [1, 2] capture social reinforcement: an agent adopts a belief (or acts on a rumor) only after a sufficient fraction of its neighbors have done so. This captures the idea that repeated exposures increase credibility and that local peer pressure matters. In economic contexts, such dynamics can model decisions to sell, to withdraw liquidity, or to propagate a rumor that affects prices or confidence [4].

This work aims to (i) present systematic simulation results on synthetic networks, (ii) validate qualitative behavior on an empirical market network constructed from daily returns of selected US equities, and (iii) discuss policy implications for monitoring and intervention.

2 Related work

Threshold models of collective behavior originate with Granovetter [1]. Watts [2] analyzed global cascades on random networks and highlighted the role of vulnerable clusters and heterogeneous degree distributions. Barabási and Albert [3] describe mechanisms for generating scale-free networks where hubs can act as superspreaders. In economic settings, Acemoglu et al. [4] study the spread of (mis)information and its welfare consequences. Empirical studies on the spread of misinformation online emphasize the role of homophily and echo chambers [5].

Our methodological approach follows these traditions by combining theoretical description, simulation, and empirical validation using market co-movement networks.

3 Model

Consider an undirected graph $G = (V, E)$ with $N = |V|$ nodes. Each node $v \in V$ has binary state $A_v(t) \in \{0, 1\}$ at discrete time t, where 1 denotes "adopted" (believes/spreads the rumor). Let $N(v)$ denote the neighborhood and $k_v = |N(v)|$ its degree. Under a homogeneous threshold $\theta \in [0, 1]$ the deterministic update rule is:

$$A_v(t+1) = \begin{cases} 1 & \text{if } A_v(t) = 1, \\ 1 & \text{if } \dfrac{1}{k_v} \sum_{u \in N(v)} A_u(t) \geq \theta, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The dynamics start from an initial seed set S_0 of fraction s_0 chosen uniformly at random. We iterate until convergence (no new adoptions) or a maximum number of steps.

Key observables are the final adoption fraction $\rho_\infty = \frac{1}{N} \sum_v A_v(T)$ and the time-to-saturation (number of steps until no further change). The model admits several extensions: heterogeneous thresholds θ_v, weighted/ directed edges, and temporally evolving networks.

4 Synthetic experiments

We simulate the threshold process on three canonical network families with $N = 2000$ and mean degree $\langle k \rangle \approx 4$ (parameters chosen to reflect sparse interaction networks):

- Erdős–Rényi (ER): $G(n, p)$ with $p = \langle k \rangle / (N - 1)$.
- Barabási–Albert (BA): preferential attachment with parameter m producing $\langle k \rangle \approx 2m$.
- Watts–Strogatz (WS): small-world with nearest neighbors k and rewiring probability p_{rewire}.

For each topology we sweep the homogeneous threshold θ on a grid between 0.05 and 0.6, and average the final adoption fraction over multiple realizations to reduce sampling variance. Initial seed fraction $s_0 = 0.01$ unless otherwise stated.

4.1 Summary of synthetic results

Consistent with previous literature, BA networks (scale-free) remain susceptible to large cascades at higher θ relative to ER and WS, due to hub-mediated reinforcement. ER networks show sharper cutoffs in cascade sizes as θ increases. WS networks exhibit intermediate behavior with clustering that can both trap and reinforce cascades depending on local structure. These qualitative conclusions are robust to moderate changes in N and s_0 (see supplementary code).

(Plots of these synthetic experiments are produced by the provided code and can be generated locally. For brevity we summarize the key outcome: heterogeneous degree distributions increase cascade probability and size.)

5 Empirical validation

We construct an empirical market network using daily adjusted close prices of selected US equities (AAPL, AMZN, GOOGL, MSFT, TSLA) over approximately one year. Let $P_{i,t}$ denote the adjusted close price for asset i on day t. We compute log-returns $r_{i,t} = \log P_{i,t} - \log P_{i,t-1}$ and the Pearson correlation matrix $C_{ij} = \mathrm{corr}(r_i, r_j)$. We place an undirected edge between i and j if $C_{ij} \geq 0.5$ (a common empirical threshold to capture moderately strong co-movement).

Figure 1 shows the correlation matrix; Figure 2 visualizes the network. Running the threshold dynamics on this graph (homogeneous θ sweep) yields the adoption curves in Figure 3 and example time-series in Figure 4.

5.1 Interpretation

The empirical network, although small, already shows that correlated clusters of assets can act as local reinforcement structures. Cascades are more likely when clusters of high intra-correlation exist; this suggests that during periods of high market correlation (e.g., crises), rumor propagation and panic propagation may be facilitated.

6 Policy implications and mitigation

Our results suggest several practical approaches to reduce systemic vulnerability to rumor-like cascades:

- Monitor high-centrality assets/agents (hubs) and flag anomalous information propagation originating near them.
- Introduce brief friction or verification delays on information propagation channels during stress periods (reducing effective exposure reinforcement).
- Design targeted counter-messaging to high-degree communities rather than broad-spectrum interventions, as local clusters amplify spread.

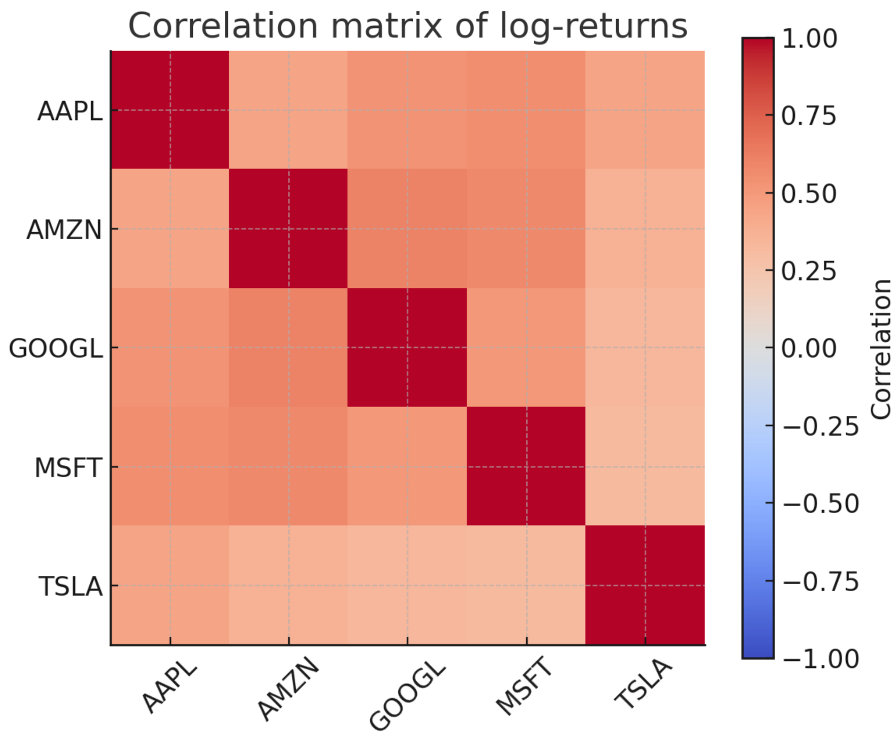

Figure 1: Correlation matrix of daily log-returns for selected US equities.

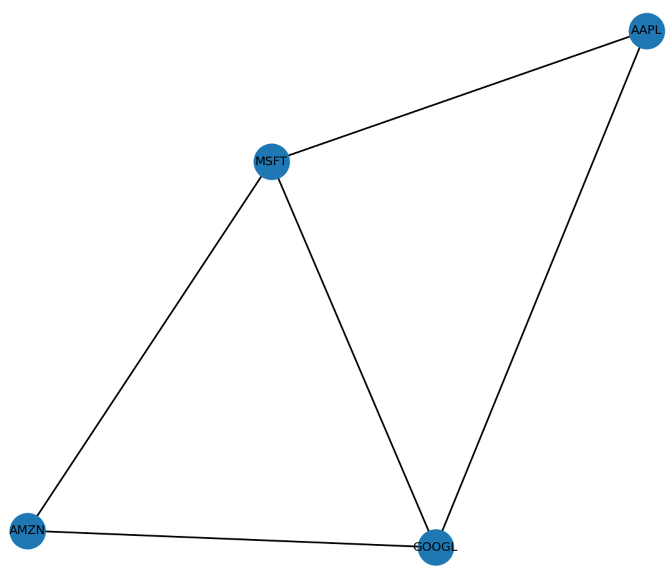

Figure 2: Empirical market network (correlation threshold 0.5).

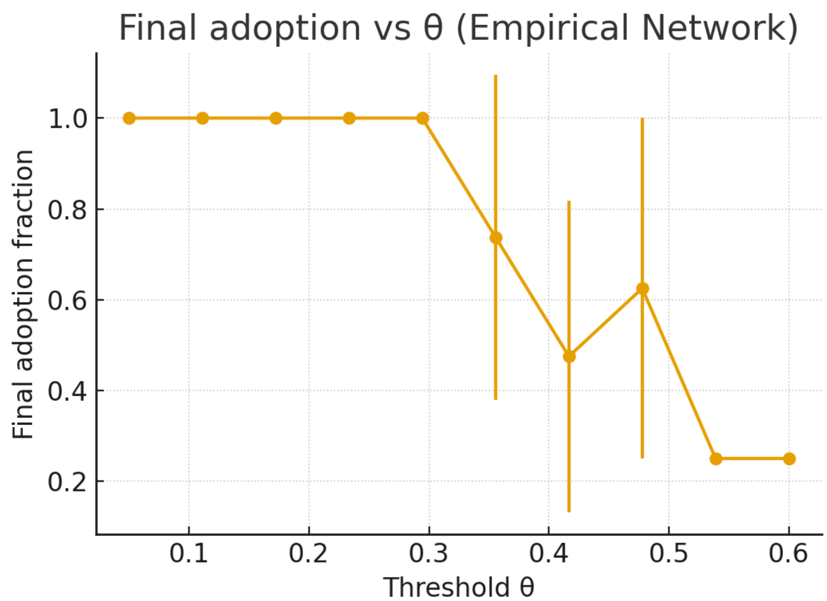

Figure 3: Final adoption fraction vs threshold θ on the empirical market network.

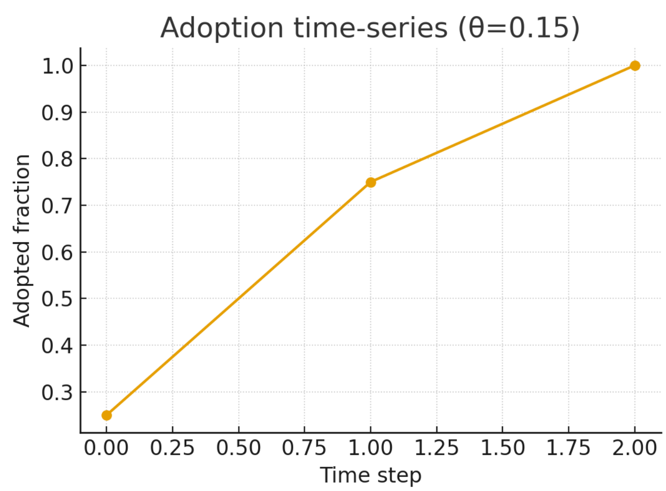

Figure 4: Example adoption time-series ($\theta = 0.15$).

7 Limitations and future work

The current study uses a small cross-section of equities and a simple correlation threshold to construct the network. Future work should: consider larger universes (e.g., entire S&P500), weighted and directed influence edges, heterogeneous thresholds estimated from agent behavior, and validation using datasets of actual rumor/news propagation (social media traces) aligned with market reactions. Temporal networks and adaptive behavior (agents changing connectivity) are natural and important extensions.

8 Conclusion

Threshold models on networks provide a parsimonious yet powerful framework to study rumor-like propagation in financial systems. Synthetic and empirical experiments both indicate that network structure — especially heterogeneity and clustering — critically shapes cascade risk. Effective monitoring and targeted interventions focusing on hubs and clusters can mitigate systemic vulnerability.

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