

Supplementary Material: Entropy-Based Indicators of Critical Transitions in Heavy-Tailed Networks Under Progressive Node Removal

S1. Fisher Information of the Residual Degree Distribution

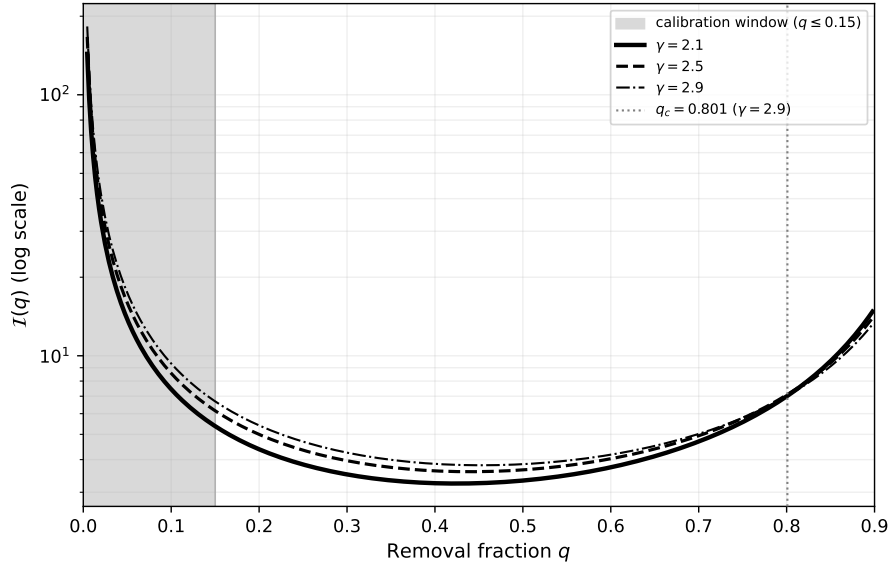


Figure S1: Fisher information $\mathcal{I}(q)$ of the residual degree distribution $\tilde{P}(k'; q)$ under random node removal, computed via central finite differences on the binomial-thinning residual (Eq. 3 of the main text), for $\gamma \in \{2.1, 2.5, 2.9\}$ (log y -axis). Shaded region: calibration window ($q \leq 0.15$); gray dotted vertical line: analytical Molloy–Reed threshold q_c for $\gamma = 2.9$ (the only case with $q_c < q_{\max} = 0.9$). $\mathcal{I}(q)$ is large at small q , reaches a minimum in the mid-damage range, then grows toward q_c , consistent with signal acceleration as the percolation threshold is approached in the population-level model. This growth toward q_c was evaluated under the discrete power-law reference P_0 specifically; it is not asserted as a general property of all heavy-tailed initial degree distributions.

S2. Reproducibility

One-command reproduction

All results can be regenerated from the repository root with:

```
bash run_docker.sh
```

This builds a Docker image with pinned dependencies and runs the full pipeline, producing `paper.pdf` and all intermediate artifacts in `paper/`. Requires Docker. The CAIDA data file (`caida_as_edges.txt`) must be obtained separately; see `README.md` in the repository for download instructions. The pipeline will skip the CAIDA step gracefully if the file is absent.

Without Docker

Individual steps can be run directly after installing dependencies (`pip install -r requirements.txt`)

```
# Chung-Lu gamma sweep
.venv/bin/python main.py

# Sensitivity table
.venv/bin/python main.py --sensitivity-only

# Configuration-model sweep (exponent-matched)
.venv/bin/python main.py --graph-model config

# Degree-sequence-matched CM diagnostic
.venv/bin/python -m runner.degree_matched_config_check
.venv/bin/python -m runner.make_degree_matched_table

# Baseline-window sensitivity analysis
.venv/bin/python -m runner.baseline_window_sensitivity

# CAIDA figure
.venv/bin/python -m runner.make_caida_fig --edges caida_as_edges.txt

# Compile PDF
latexmk -pdf paper.tex
```

S3. Sensitivity to Smoothing and Threshold

This table reports sensitivity of warning timing to α and z under the fixed decision rule ($\gamma = 2.5$, 40 seeds). Values are mean $\pm$ std with detection counts n_{det}/n .

Table S1: Sensitivity of random-failure warning timing to EWMA smoothing α and baseline threshold z in the rule $\tilde{D}_{\text{KL}} > \mu_0 + z\sigma_0$. Values report mean $\pm$ std across seeds (with n_{det}/n counts).

α	z	γ	q_{warn} (mean $\pm$ std) [n_{det}/n]	Δ_{warn} (mean $\pm$ std) [n_{Δ}/n]
0.10	1.5	2.5	0.174 ± 0.023 [40/40]	0.653 ± 0.034 [40/40]
0.10	2.0	2.5	0.215 ± 0.044 [40/40]	0.612 ± 0.049 [40/40]
0.10	2.5	2.5	0.284 ± 0.094 [40/40]	0.542 ± 0.094 [40/40]
0.20	1.5	2.5	0.216 ± 0.056 [40/40]	0.610 ± 0.059 [40/40]
0.20	2.0	2.5	0.297 ± 0.111 [40/40]	0.529 ± 0.111 [40/40]
0.20	2.5	2.5	0.443 ± 0.179 [39/40]	0.382 ± 0.179 [39/40]
0.30	1.5	2.5	0.230 ± 0.077 [40/40]	0.596 ± 0.077 [40/40]
0.30	2.0	2.5	0.306 ± 0.132 [40/40]	0.520 ± 0.130 [40/40]
0.30	2.5	2.5	0.447 ± 0.168 [39/40]	0.379 ± 0.168 [39/40]

S4. Moment-Based Benchmark: Baseline Deviation on $\kappa(q)$

This benchmark applies the same EWMA smoothing ($\alpha = 0.20$) and baseline-deviation rule ($z = 2$, $q_0 = 0.15$) to the Molloy–Reed branching factor $\kappa(q) = (\langle k^2 \rangle_q - \langle k \rangle_q) / \langle k \rangle_q$ as a low-order-moment comparator. Results show 0/40 detections at $\gamma = 2.5$, confirming that matching the first two moments is insufficient to detect the pre-collapse distributional reorganization captured by successive KL divergence.

Table S2: Moment-based benchmark under random failure. We apply the baseline-deviation rule to the EWMA-smoothed Molloy–Reed branching factor $\tilde{\kappa}(q)$ (baseline window $q \leq 0.15$, $\alpha = 0.20$). We report q_{warn}^{κ} , $\Delta_{\text{warn}}^{\kappa} = q_{\text{collapse}} - q_{\text{warn}}^{\kappa}$, detection counts (n_{det}/n), and the baseline-referenced $Z_{\text{max}}^{\kappa} = \max_q (\tilde{\kappa}(q) - \mu_0) / \sigma_0$ as mean $\pm$ std across seeds (Chung–Lu, $N = 10,000$, $\gamma = 2.5$).

γ	q_{warn}^{κ} (mean $\pm$ std)	(n_{det}/n)	$\Delta_{\text{warn}}^{\kappa}$ (mean $\pm$ std)	Z_{max}^{κ} (mean $\pm$ std)
2.5	–	(0/40)	–	1.219 ± 0.284

S5. Configuration-Model Graph Construction Details

Detection results and mechanistic interpretation for the configuration-model experiments are reported in the main Results section. Construction details are provided here.

Exponent-matched CM (main experiment)

A target degree sequence is drawn from a discrete power-law distribution with exponent γ and minimum degree $k_{\text{min}} = 1$, truncated to $N = 10,000$ nodes. The sequence is passed to the configuration-model stub-matching procedure; self-loops and parallel edges are removed; and the experiment is conducted on the largest connected component. Each (γ , seed) run uses an independently sampled degree sequence.

Sequence-matched CM (degree-matched diagnostic)

For each $(\gamma, \text{cl_seed})$ pair, a Chung–Lu graph G_{CL} is generated and its realized degree sequence $\mathbf{d}$ is extracted. Multiple CM wiring replicates are then constructed from $\mathbf{d}$ (varying only the stub-pairing seed), producing CM graphs with the exact same degree sequence as the CL source. Self-loops and parallel edges are removed and the experiment is conducted on the largest connected component. This design controls for the degree sequence and isolates the effect of the hard-constraint wiring mechanism.