I have no idea how GitHub works, so I can add only posts like this. :D

So I took 3 of the sources and gave them to ChatGPT to summarise, because I understood nothing when I tried to go through them. :D

I found 5 relevant sources in total (one could not be downloaded).

My idea would be to take the S&P 500 index (it is an index showing how the 500 biggest US companies are doing) and compare it before and after a crisis. I propose to deal with two crises: the one in 2008, and the big downfall when Trump became president.

I would stick to correlations and the threshold method. It is the most used in the papers.

All of these papers deal with static networks and handle time dependency when working with correlations. I did not absolutely understand the approaches, but I think it will be more reasonable than trying to deal with time-dependent networks.

What do you think?

Below is a focused summary of each of the three papers, with particular emphasis on (1) what they do, (2) how they build their networks, (3) how they handle the fact that the underlying data are time-indexed (i.e. "time-dependent"), and (4) whether and how they work with simple correlations.

1. Barigozzi & Hallin (2017): *"A network analysis of the volatility of high-dimensional financial series"*

What they do:
They study daily volatilities (not returns) of the S&P100 constituents over 2000–2013, focusing on the 2007–08 crisis. Their goal is to assess "who shocks whom" in volatility, i.e. volatility-contagion networks.

Network construction:

1. **Extract volatilities** from returns (via a realized-volatility or proxy; see their Section 4).
2. **"Factor + sparse VAR" approach:**
   - **Step 1:** Fit a **generalized dynamic factor model (GDFM)** to strip out common ("market") volatility shocks, leaving idiosyncratic volatility series.
   - **Step 2:** On the idiosyncratic series, estimate a **sparse VAR** (they try elastic net, group-lasso, adaptive-lasso).
   - **Step 3:** Invert the VAR to get a Vector-MA representation; from the MA coefficients they form the **Long-Run Variance Decomposition Network (LVDN)**, where the weight on edge ($i \to j$) is the proportion of i's forecast-error variance due to shocks in j.

Time-dependence:
Although they analyze two subperiods (2000–13 vs. 2007–08), **within each window the network is treated as static**. There is no rolling-window or explicit time-varying network; rather, they build one (static) LVDN per period.

Correlations?
They do *not* build a simple correlation-threshold network. Instead they exploit **variance–decomposition** from a VAR of volatilities, which goes beyond raw correlations to capture directional, dynamic spillovers.

2. Namaki et al. (2011): *"Network analysis of a financial market based on genuine correlation and threshold method"*

What they do:
They study stock-return correlations in the Tehran Stock Exchange (and test on DJIA), aiming to "clean" out the overall market movement and then explore the topology of the remaining correlations.

Network construction:

1. Compute the usual **equal-time Pearson correlation matrix** of returns.
2. **"Remove the market mode"** by regressing each return $G_i(t)$ on the first principal component (largest-eigenvalue eigenvector) of the correlation matrix—i.e. the CAPM-style one-factor model—and retain the residuals.
3. Recompute the **"cleaned" correlation matrix** from these residuals.
4. For a chosen threshold θ, draw an **undirected edge** between stocks i and j whenever the cleaned $\mathrm{Corr}_{ij} \geq \theta$.

They then vary θ to study degree distributions, clustering, component counts, etc.

Time-dependence:
This is a **static, single-period** snapshot. There is no sliding-window or time-varying network; all statistics are aggregated over the full sample.

Correlations?
Yes. *This* paper is all about simple pairwise Pearson correlations (albeit "cleaned") and threshold-based graph construction.

3. Kumar & Deo (2012): *"Correlation and network analysis of global financial indices"*

What they do:
They analyze 20 country-level equity indices around the world, comparing the pre-2007 "calm" period to the crisis period.

Network construction (multiple layers):

- **RMT analysis:** Compute correlation matrices in **sliding-window blocks** (25 trading days) to track the evolution of eigenvalues/eigenvectors (and IPR) over time. This is purely diagnostic.

- **Threshold networks:** For each of the two periods (pre-crisis vs. crisis), compute the static correlation matrix, then for various thresholds draw undirected graphs (using Fruchterman-Reingold layout) to see clustering by region.

- **Minimum Spanning Tree (MST):** Build an MST from the distance metric $d_{ij} = \sqrt{2(1 - C_{ij})}$ for each period to reveal hierarchical "backbone" structure.

- **Hierarchical clustering:** Apply average-linkage dendrograms and report cophenetic correlation coefficients, comparing how "hierarchical" the market is pre- vs. during crisis.

Time-dependence:

- **Explicitly** handled in the RMT part via **rolling windows**: they track how the largest eigenvalues (and the clustering in the 2nd eigenvector) evolve day by day.

- The **networks themselves**, however, are *static* within each of the two broad periods (pre-crisis and crisis).

Correlations?

Yes—this is also a classic **correlation-threshold** and MST-based network, built off raw Pearson correlations of returns.

How "time-dependency" is handled, side by side

Paper	Dynamic network?
Barigozzi & Hallin (2017)	No rolling/temporal network—two snapshots only (2000–13 vs. 2
Namaki et al. (2011)	No
Kumar & Deo (2012)	Partly: RMT uses sliding windows; but threshold/MST nets are

Correlations versus VAR/variance–decomposition

- **Barigozzi & Hallin** go beyond raw correlations: they model volatilities via a **sparse VAR** (after factor-filtering) and use the **forecast-error variance decomposition** to measure directed links.

- **Namaki** and **Kumar & Deo** both build undirected graphs **directly from Pearson correlations** (with Namaki first "cleaning" out the market factor).

In your own study

Since you plan to look at S&P500 stocks across "before-2008 crisis" vs. "crisis" vs. "pre-Trump" vs. "post-Trump," and you're wary of fully time-dependent (sliding-window) networks, you have two main options:

1. **Static snapshots**, à la all three papers, where you build one network per subperiod—either via correlation-threshold (Namaki; Kumar & Deo) or via VAR-based variance decomposition (Barigozzi & Hallin).

2. **Rolling/windows** only if you need to see gradual evolution (as in the RMT part of Kumar & Deo).

If you stick to static networks, you avoid the complexity of time-varying parameter estimation—and for correlations, you'll be in good company with Namaki and Kumar & Deo. If you want directional, dynamic spillovers, follow Barigozzi & Hallin's **factor + sparse VAR** pipeline, but still estimated separately in each period.