Comparing Crobex Network Structures Under Different Correlation Filtering Methods

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Abstract

Financial markets are complex systems, and one way to better understand them is to examine how different stocks are connected. This study examines how various methods for filtering correlations between stock returns can influence the structure of financial networks. For the Croatian stock market, three popular filtering approaches are compared: p-value thresholding based on partial correlations, False Discovery Rate (FDR) correction, and shrinkage estimation. Two very different time periods are examined: the 2008 financial crisis and a calmer market phase in 2023. To avoid noise from overall market movements, the common market component is removed and the focus is on residual, or idiosyncratic, returns. This helps reveal more specific connections, less driven by broad trends. The results show that filtering choices matter a great deal: the p-value method does the best job at highlighting meaningful changes between the two periods, showing stronger clustering and structure during the crisis. Shrinkage filtering, on the other hand, often produces dense but harder-to-interpret networks, whereas FDR tends to be overly cautious, especially in smaller markets. These insights are valuable for researchers and practitioners trying to use network analysis to track market behaviour, stress, or structural change over time.

Keywords: financial networks; correlation filtering; CROBEX; partial correlation; network topology; market structure

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Introduction

In financial market analysis, network-based approaches are increasingly being used because they provide information about the structural dependencies among financial instruments. More recently, network-based approaches have been refined to explicitly measure systemic risk. For example, Hasse (2022) introduces a network-based systemic risk measure that accounts for both direct and indirect interconnections, showing that indirect links tend to amplify during systemic events. This is conceptually related to risk models, which emphasize interdependencies among financial institutions beyond correlation matrices (Li & Zhang, 2024), offering complementary perspectives on network formation and contagion. These techniques are especially effective for identifying latent market structures, evaluating diversification opportunities, and assessing systemic risks. In this work, a correlation network methodology is employed to examine the structure of the Croatian stock market under various statistical filtering techniques. Three common filtering strategies are employed: p-value thresholding of pairwise Spearman correlations (interpreted as partial correlations after market factor removal), False Discovery Rate (FDR) correction, and shrinkage estimation with hard thresholding.

The most liquid equities listed on the Zagreb Stock Exchange make up the CROBEX index, which serves as the primary benchmark for the Croatian equity market. The Croatian market provides an interesting case study for evaluating correlation-based network filtering, given its comparatively modest size and industry concentration. Knowing its internal structure makes it easier to identify possible directions for contagion, the possibilities of diversification, and how prominent stocks influence market dynamics as a whole. Two samples serve as the basis for this analysis: one capturing the two CROBEX revisions from 2008 (between March 24, 2008, and March 20, 2009), and the other capturing the two 2023 revisions periods (between March 20, 2023, and March 15, 2024). This study examines and compares network properties during periods of increased market scrutiny and realignment, enabled by these windows, which capture significant moments of structural rebalancing.

The generated networks are compared over two periods and three degrees of significance or filtering severity (0.01, 0.05, and 0.1) to show how the choice of filtering method, parameter, and market regime affects network structure and average node-level metrics. These results offer guidance for the empirical use of network analysis in financial studies, particularly when balancing resilience and interpretability.

Data and methodology

Two time periods are considered: one corresponds to one of the two 2008 revisions, which occurred between March 24 and March 20, 2008, and the other to one of the two 2023 revisions, which occurred between March 2023 and March 15, 2024. The dataset was created from historical daily stock prices of all securities included in the CROBEX at any given time.

To ensure data authenticity, stocks with a high proportion of missing values are removed (only those traded for at least two-thirds of the observed time period are retained). The real comparable return of the stock is represented by idiosyncratic (specific, residual) returns. Specifically, excess returns are calculated by performing linear regression of each stock's return on the market factor (CROBEX returns) and obtaining the residuals. The resulting dataset thus captures idiosyncratic components of returns, which are more suitable for identifying meaningful inter-stock relationships that are not driven by market-wide dynamics. Then, the network analysis is performed on the correlations among idiosyncratic returns.

Therefore, this process consists of computing partial correlations after market factor removal introduced by Xu et al. (2017). These correlations form the input to the construction of adjacency matrices and networks, after being filtered by three different approaches:

- P-value of Partial Correlation (PC): This method sets correlation entries to zero when the associated Spearman correlation p-value exceeds a given α. As applied to residual returns, this approach is analogous to the p-filtering approach for partial correlations proposed by Xu et al. (2017).
- False Discovery Rate (FDR) Control: Here we apply the Benjamini-Hochberg procedure to adjust p-values and control the expected proportion of false positives. The adjusted threshold retains only statistically significant correlations under controlled FDR. This approach has gained popularity in high-dimensional settings such as genomics and finance, due to its balance between sensitivity and specificity (Benjamini & Hochberg, 1995).
- Shrinkage Estimation (SE): The shrinkage estimator of the correlation matrix provides a regularized estimate less sensitive to sampling noise. A hard threshold is applied to the absolute values of the entries of the shrinkage correlation matrix, setting entries below the threshold to zero. This approach, introduced by Schäfer and Strimmer (2005), is beneficial in small sample, high-dimensional data scenarios.

These methods yield different correlation matrices, which are then used to build undirected weighted networks. A network is constructed to gain deeper insight into the relationships among stocks. The links are weighted to reflect the strength of the correlations and are color-coded to distinguish between positive and negative associations. To examine the network's topological features, key metrics such as graph density, structural characteristics, centrality measures, and community detection metrics were calculated. These measures, commonly used in network analysis (e.g., Newman, 2010; Barabási, 2016; Xu et al., 2017; Battiston et al., 2012), help identify important nodes, structural connections, and weak points in the network, providing insights into systemic stability and market behavior.

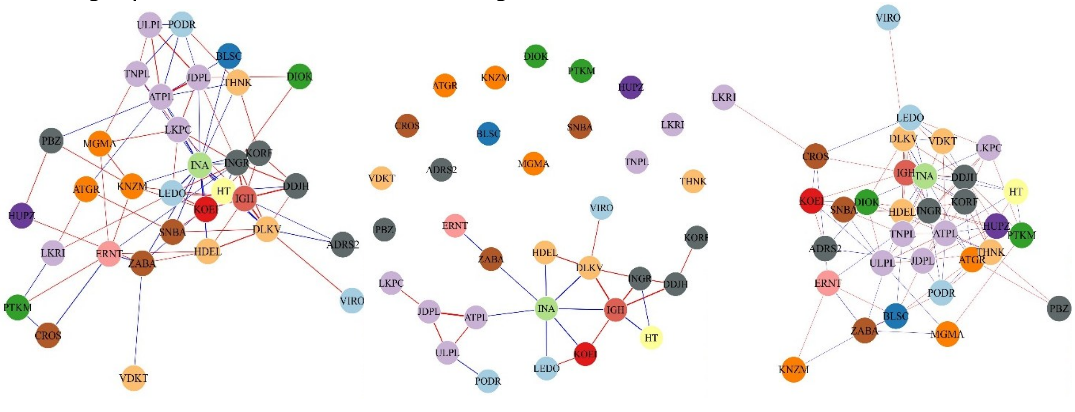
Graph density indicates the ratio of actual links to all possible links in the graph, providing an overall picture of network connectedness. Assortativity represents the correlation between the degrees of connected nodes. It reveals whether nodes tend to connect with others of similar degree, for example, whether highly connected stocks are linked to each other. Clustering coefficients measure the tendency of nodes to form closed groups, while the average shortest path between any two nodes reflects the efficiency of information transfer within the network. Node centrality measures were calculated to assess the influence of individual stocks within the network. Degree centrality counts the number of direct connections, while weighted centrality also considers the strength of these links. Betweenness centrality shows how often a node appears on the shortest paths between other nodes. Closeness centrality measures how close a node is to all others, i.e., how quickly it can reach the rest of the network. Eigenvector centrality also rewards nodes connected to other influential nodes. The average values of these measures offer insight into the distribution of influence within the network.

To identify communities, the fast-greedy modularity optimization algorithm by Blondel et al. (2008) was used. In this context, modularity measures how well the network can be divided into groups with dense internal links and sparser intergroup links. In contrast, the number of nodes in each group determines community size. Modularity compares the actual number of within-group connections to the expected number under random linking. All analyses, from data preparation to network construction, were conducted in the R software environment (R Core Team, 2024).

Results

To provide an intuitive understanding of the structural differences, Figure 1 presents the networks constructed under each method for alpha = 0.05. Node colours indicate sectoral affiliation. The p-thresholding method yields a sparser, more modular structure, while shrinkage filtering tends to produce denser networks.

Figure 1
Network graphs under different filtering methods: PC, FDR, SE



Source: Author’s illustration

To evaluate how the filtering method and threshold affect the resulting network, a comprehensive set of network-level and averaged node-level metrics is computed. The results for key network metrics under all methods and all three thresholds for the 2008 interval are summarized in Table 1.

Table 1
Summary of Network-Level Metrics Across Methods and Thresholds for 2008 Revisions

Metric	PC (0.01)	FDR (0.01)	SE (0.01)	PC (0.05)	FDR (0.05)	SE (0.05)	PC (0.1)	FDR (0.1)	SE (0.1)
Nodes	33	33	33	33	33	33	33	33	33
Edges	40	16	414	88	25	103	120	36	3
Density	0.076	0.030	0.784	0.167	0.047	0.195	0.227	0.068	0.006
Assorta-tivity	0.053	-0.244	-0.059	-0.039	-0.073	0.057	-0.017	0.024	NA
Avg. Degree centrality	2.424	0.970	25.091	5.333	1.515	6.242	7.273	2.182	0.182
Strength Centrality	0.549	0.271	0.935	0.985	0.383	0.418	1.218	0.508	0.207
Av. Correlation	0.169	0.101	0.037	0.177	0.131	0.065	0.162	0.162	0.010
Av. Between Centrality	18.333	0.848	11.121	213.04	8.454	18.27	16.21	12.424	0
Eigenvalue centrality	0.202	0.147	0.632	0.304	0.181	0.351	0.345	0.198	0.090
Modularity	0.446	0.388	0.112	0.366	0.450	0.304	0.266	0.445	0.005
Av. clustering coefficient	0.425	0.773	0.788	0.431	0.486	0.314	0.394	0.451	1

Source: Author's work

The results show that shrinkage-based filtering produces dense networks with high clustering and low modularity. P-thresholding results in sparser, more modular, and somewhat assortative networks, especially at more conservative levels (α = 0.01). FDR-filtered networks tend to be low-density.

These findings indicate that the choice of filtering method and significance level has a substantial impact on both the network topology and the rankings of node centrality. From a practical standpoint, the p-thresholding method (interpreted as partial-correlation filtering after factor removal) yields a more conservative network than shrinkage, emphasizing only the most robust dependencies. This is especially useful for identifying strong sectoral clusters or stable connections.

To observe how networks behave across different market regimes, Table 2 summarizes the network metrics results for the 2023 interval across all methodologies and all three thresholds.

Table 2
Summary of Network-Level Metrics Across Methods and Thresholds for 2023 Revisions

Metric	PC (0.01)	FDR (0.01)	SE (0.01)	PC (0.05)	FDR (0.05)	SE (0.05)	PC (0.1)	FDR (0.1)	SE (0.1)
Nodes	20	20	20	20	20	20	20	20	20
Edges	5	1	181	16	1	135	23	3	91
Density	0.026	0.005	0.953	0.084	0.005	0.711	0.121	0.016	0.479
Assorta-tivity	-0.739	NA	-0.093	-0.226	NA	-0.059	0.072	-1	0.090
Avg. Degree centrality	0.5	0.1	18.1	1.6	0.1	13.5	2.3	0.3	9.1
Strength Centrality	0.116	0.029	1.897	0.306	0.029	1.753	0.403	0.078	1.428
Av. Correlation	0.067	0.029	0.104	0.147	0.029	0.128	0.151	0.052	0.157
Av. Between Centrality	0.65	0	8.7	9.2	0	5.15	17.35	0.15	6.15
Eigenvalue centrality	0.162	0.1	0.720	0.215	0.100	0.687	0.250	0.136	0.597
Modularity	0.147	0	0.102	0.483	0	0.129	0.409	-0.006	0.189
Av. clustering coefficient	0	NA	0.951	0.308	NA	0.761	0.071	0	0.627

Source: Author's work

While the relative performance of filtering methods is preserved, the 2023 period shows slightly lower modularity and higher connectivity in some filtering methods, possibly reflecting a more integrated market structure in recent years. Nevertheless, under p-thresholding at $\alpha = 0.05$, sectoral clustering remains visible, and assortativity is still positive, indicating that the basic structural segmentation persists. These findings suggest some continuity in the internal architecture of the CROBEX network, while also hinting at evolving market dynamics. Another explanation for this could be the overall decline in market liquidity in 2023, which concentrates trade in fewer stocks and industries, resulting in the formation of more clearly defined communities within the network.

Discussion

Observing the 2008 results, FDR-based filtering offers a statistical balance, retaining meaningful structure while controlling for multiple testing. Shrinkage-based networks provide a richer structure, which helps capture subtler dependencies, though possibly at the cost of interpretability and higher false discovery rates. The differences in assortativity and clustering metrics also imply that the choice of filtering can influence the inferred contagion channels or systemic vulnerability structures. For example, positive assortativity observed in partial correlation networks suggests a homophilic structure, possibly driven by sectors. In contrast, shrinkage networks with low or negative assortative may represent more diverse and less interpretable interconnections.

The structure of the CROBEX network under conservative p-thresholding appears to exhibit sectoral clustering with moderate modularity, indicating a relatively segmented market structure. In contrast, the dense shrinkage-based network lacks modular separation, suggesting blurred sectoral boundaries and potential overconnectivity.

Compared with previous findings in more developed markets (e.g., Xu et al., 2017), the modularity and assortativity of the Croatian market under conservative filtering appear relatively high, indicating pronounced segmentation and sector-specific cohesion. However, under lenient or regularized filtering (e.g., shrinkage at 0.01), the CROBEX network becomes nearly fully connected, with average degrees exceeding 25 and a density over 75%, suggesting a less interpretable structure and possibly overestimated interdependence. Such divergence highlights the need for cautious interpretation of dense networks.

To assess which filtering method most effectively distinguishes between the crisis period of 2008 and the calmer environment of 2023, the focus is on network-level metrics that are independent of the number of nodes, such as density, modularity, assortativity, average clustering coefficient, and normalized centralities. These measures allow meaningful comparisons even though the 2008 network includes 33 stocks while the 2023 network contains only 20.

The p-value thresholding method (interpreted as a proxy for partial correlation after market-factor removal) reveals the most evident contrast between the two market regimes. In 2008, networks filtered at α = 0.01 exhibit higher density (0.076) and modularity (0.446), while in 2023, both values drop considerably (density = 0.026, modularity = 0.147). This suggests a more segmented and interconnected structure during the crisis, consistent with literature describing heightened sectoral clustering and reduced diversification during systemic stress. Additionally, assortativity shifts from a slightly positive value in 2008 (0.053) to strongly negative in 2023 (–0.739), indicating a reversal from sectorally cohesive clusters to more heterogeneous, less structured linkages. Clustering coefficients also drop markedly, from 0.425 in 2008 to zero in 2023, reinforcing the interpretation that the 2023 market was more diffuse and less tightly interconnected.

FDR-adjusted filtering, although theoretically appealing for its control of false positives, exhibits extremely sparse connectivity in both years, especially in 2023, where the average clustering coefficient and assortativity are effectively zero or undefined. This lack of structural signal suggests that the method may be overly conservative, particularly in smaller emerging markets or during calm periods, thereby suppressing meaningful dependencies even when they are present.

Shrinkage-based filtering, by contrast, produces networks that are densely connected in both periods, with average clustering coefficients consistently above 0.75 and low modularity (e.g., 0.112 in 2008 and 0.102 in 2023 at α = 0.01). Although this method preserves many weak correlations, the resulting networks show limited differentiation between regimes. The density is actually higher in the 2023 network (0.953) than in the 2008 one (0.784), which is counterintuitive if the goal is to capture increased market interconnectedness during crises. These findings imply that shrinkage filtering, while effective in reducing estimation noise, tends to obscure regime-dependent structural shifts and may overestimate interdependence. On the other hand, shrinkage estimators effectively reduce sample-specific fluctuations by stabilizing noisy correlation matrices, pulling extreme values toward a predefined target, typically the identity matrix. Only the most reliable correlations that exceed a given threshold are retained when a hard threshold is later applied to the absolute values of the shrinkage-adjusted correlations. In contrast to p-value-based filtering techniques, sparser networks result from discarding numerous weak but stable linkages as the threshold rises. Because regime-dependent structural variation is suppressed by this two-step stabilizing and aggressive pruning process, networks from crisis periods tend to resemble those from calmer periods. By filtering out not only estimation noise but also a large portion of the regime-specific signal, thresholder shrinkage effectively produces networks that represent long-term, low-volatility interactions rather than short-term, crisis-induced interdependencies. By smoothing over structural shocks and possibly muting signs of systemic stress, this method offers a more uniform and conservative perspective of financial linkages than "removing" crises completely. Shrinkage-based filtering may therefore be especially well-suited to uncovering underlying, stable inter-firm relationships that endure across various market conditions and are not just the result of transient turbulence or widespread market co-movement, such as supply chain ties, business alliances, or sectoral cohesion. In contrast, the p-thresholding method is the most sensitive to underlying regime changes. It reflects both the increased clustering and segmentation typical of crisis periods and the looser, more fragmented structure in calmer times.

Conclusion

This study compares correlation network structures in the Croatian equity market using three prominent filtering methods: p-thresholding, FDR adjustment, and shrinkage estimation. The methods are applied to two distinct time periods: the crisis-affected year 2008 and the relatively stable year 2023. By focusing on residual correlations after removing market-wide effects, a cleaner view of the idiosyncratic relationships among CROBEX constituents is obtained, and networks that reflect direct structural dependencies are constructed.

The findings confirm that the choice of filtering method and threshold level significantly shapes the inferred network topology, with implications for how we interpret market segmentation, systemic risk, and contagion potential. Shrinkage filtering produces densely connected, high-clustering networks in both periods, suggesting that it retains a wide range of weak correlations but may overstate connectivity, especially in less liquid markets. In contrast, FDR filtering, while statistically conservative, results in extremely sparse networks that often fail to capture interpretable structure, particularly during calm periods or in smaller datasets such as Croatia's.

The p-thresholding method with partial correlation is the most robust at reflecting underlying market conditions—the p-thresholding method consistently captured regime shifts across these measures. In contrast, shrinkage filtering appeared insensitive primarily to the differences between 2008 and 2023, and FDR filtering filtered out nearly all meaningful signals in the more tranquil regime.

However, another contribution of this study is to highlight an alternative potential role for shrinkage-based filtering. While it tends to obscure regime-specific structural changes, its smoothing properties may make it particularly effective for identifying persistent, low-volatility relationships that transcend temporary shocks. By filtering out both noise and regime-induced spikes, shrinkage filtering may offer a conservative lens for uncovering stable inter-firm ties such as sectoral alignment, supply chain connections, or long-term strategic linkages that are not artifacts of market-wide turbulence. This perspective suggests that the value of a filtering method depends not only on its ability to reflect current market states but also on the specific analytical objectives, whether one aims to detect structural stress or isolate enduring relationships.

In the context of the CROBEX market, this implies that partial correlation filtering not only provides the best trade-off between sparsity and interpretability but also aligns well with known characteristics of financial stress. These findings offer guidance for both academics and practitioners conducting network-based analysis in emerging or thin markets, particularly in choosing filtering methods that faithfully reflect structural transitions over time.

Future work could extend this comparative framework to additional time periods or other regional markets to test the generalizability of these conclusions and explore dynamic shifts in financial network structure under different economic conditions.

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