Network-Based Portfolio Optimization from Denoised Financial Correlation Matrices

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Extended Abstract

Motivation. Network representations have become an important framework for understanding financial markets, as correlation-based networks reveal systemic risk, hierarchical organization and mesoscopic market structure [1, 3]. However, empirical correlation matrices estimated from financial returns are strongly affected by finite-sample noise, which can obscure genuine dependencies among assets and distort network topology as well as portfolio construction [5]. Random Matrix Theory (RMT) provides a principled approach to address this issue by separating meaningful correlations from random fluctuations through spectral analysis of the empirical correlation matrix [2]. In this framework, the largest eigenvalue captures collective market behavior, a few eigenvalues beyond the Marchenko–Pastur bounds represent sectoral interactions, while the remaining eigenmodes are largely dominated by noise [1].

Motivated by recent advances in network-based portfolio optimization, this study investigates whether denoised correlation matrices can generate more reliable financial networks and improve portfolio construction. In particular, we focus on the core–periphery (CP) structure, which separates densely connected core assets from sparsely connected peripheral assets [4]. Identifying such mesoscale structures can provide insights into market organization and may lead to improved diversification and risk-adjusted portfolio performance.

Methodology. We analyze daily closing prices of stocks from three major equity markets: the NIFTY 200, NIFTY 500 (India) and the S&P 500 (U.S.) from January 2010 to December 2022. After removing stocks with missing observations, the final datasets consist of 140 stocks for the NIFTY 200, 312 for the NIFTY 500 and 425 for the S&P 500. For each stock i, daily logarithmic returns are computed and normalized to account for heterogeneous volatility across assets.

From the normalized returns we construct the cross-correlation matrix C_{ij}. To reduce noise due to finite sampling, Random Matrix Theory (RMT) is used to compare the empirical eigenvalue spectrum with the Marchenko–Pastur bounds. Eigenmodes outside these bounds are retained as statistically significant, while the remaining modes are treated as noise. This decomposition yields a structured correlation matrix C^{STR} capturing meaningful market dependencies and a random component C^{RAN}. Financial networks are constructed from C^{STR} and their core–periphery structure is analyzed to guide portfolio construction and performance evaluation.

Results. Using rolling windows of 500 trading days, we construct the full correlation matrix (C^{FULL}) and the denoised structured matrix (C^{STR}) for the NIFTY 200, NIFTY 500 and S&P 500 datasets over the period 2010–2022. Financial networks derived from these matrices are analyzed using a random-walk based core–periphery detection method [4] to identify influential core and peripheral assets. Portfolios are then constructed from the top-M core or peripheral stocks ($M = 10, 20, 30, 40$) and evaluated out-of-sample over the subsequent 125 trading days under both equal-weighted and Markowitz allocation schemes.

Table 1 reports representative results for equal-weighted portfolios based on the NIFTY 200 dataset. Similar patterns are observed for the NIFTY 500 and S&P 500 datasets as well as under the Markowitz weighting scheme. Here, $\boldsymbol{\pi}_p^{\mathrm{FULL}}$ and $\boldsymbol{\pi}_p^{\mathrm{STR}}$ denote portfolios constructed from peripheral stocks identified from the full correlation network C^{FULL} and the denoised structured network C^{STR}, respectively; $\boldsymbol{\pi}_c^{\mathrm{FULL}}$ and $\boldsymbol{\pi}_c^{\mathrm{STR}}$ represent the corresponding core-stock portfolios. $\boldsymbol{\pi}^{\mathrm{HSR}}$ denotes the portfolio formed from stocks with the highest individual Sharpe ratios, $\boldsymbol{\pi}^{\mathrm{RND}}$ represents a randomly selected portfolio and $\boldsymbol{\pi}^{\mathrm{MKT}}$ corresponds to the market portfolio including all stocks in the index.

In conclusion, portfolios constructed from the denoised network C^{STR} consistently achieve superior risk-adjusted performance compared with those derived from the full correlation matrix C^{FULL}. In particular, portfolios composed of peripheral stocks exhibit stronger diversification and higher Sharpe ratios across different markets and portfolio sizes. These findings remain robust during periods of elevated market volatility, including the COVID-19 crisis. Comparisons with benchmark strategies further confirm that combining correlation denoising with core–periphery based asset selection provides a stable and effective portfolio construction framework.

Conclusions. Portfolios constructed from denoised correlation networks, particularly those composed of peripheral assets, achieve consistently higher Sharpe ratios and lower volatility than portfolios derived from full correlation matrices and standard benchmark strategies. These results demonstrate that integrating correlation denoising with core–periphery based asset selection provides a robust and efficient framework for portfolio construction.

Table 1: Sharpe ratio comparison of equal-weighted portfolio strategies for portfolio sizes $M = \{10, 20, 30, 40\}$ over a holding horizon of $T = 120$ trading days using NIFTY 200 stocks. Note: Similar results are obtained for the NIFTY 500 and S&P 500 datasets and under the Markowitz weighting scheme.

M	$\boldsymbol{\pi}_p^{FULL}$	$\boldsymbol{\pi}_p^{STR}$	$\boldsymbol{\pi}^{HSR}$	$\boldsymbol{\pi}^{RND}$	$\boldsymbol{\pi}^{MKT}$	$\boldsymbol{\pi}_c^{FULL}$	$\boldsymbol{\pi}_c^{STR}$
10	0.6525	0.6042	0.4663	0.6493	*0.5088*	0.1864	0.1841
20	0.6827	**0.7723**	0.4755	0.5822	*0.5088*	0.2108	0.1893
30	0.7097	**0.8054**	0.4923	0.5481	*0.5088*	0.2397	0.1974
40	0.7187	**0.8097**	0.4921	0.5360	*0.5088*	0.2733	0.2268

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