THE INTEGRATION OF NETWORK CONNECTEDNESS INTO PORTFOLIO OPTIMIZATION: A LITERATURE REVIEW

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Abstract: ***This literature review explores the integration of network topology into portfolio optimization frameworks. By conceptualizing financial markets as interconnected systems of nodes and links, researchers leverage graph theory to uncover hidden systemic dependencies and enhance risk management. The review synthesizes diverse methodologies, including Minimum Spanning Trees, Planar Maximally Filtered Graph and multilayer synthetic networks. A central debate concerns the systemic dimension of assets: while evidence from mature markets suggests a negative relationship between asset centrality and optimal portfolio weights, emerging digital industries like blockchain present contradict results. In these innovation-driven sectors, the resource-based view indicates that central firms possess superior resource access and innovation capability, signaling quality over systemic risk. Evaluating vulnerabilities across different economies, this review identifies several literature gaps and suggests a roadmap for future research.***

• Keywords: *network topology, centrality measures, portfolio optimization, systemic risk, asset allocation.*

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1. Introduction

The traditional paradigm of portfolio selection, pioneered by the seminal work of Harry Markowitz in 1952, has historically focused on the trade-off between expected returns and their variance. While Modern Portfolio Theory provided the foundational mathematical framework for asset allocation, its practical application has often been undermined by the error-maximizing property of mean-variance optimization, where small inputs' estimation errors lead to large variations in optimal weights. In response to these limitations, a growing field of research has emerged that characterizes financial markets not merely as a collection of assets, but as a complex network of interconnected nodes and links. This review examines the integration of network theory and portfolio optimization, a synthesis that seeks to leverage the topological properties of financial systems to enhance risk management and investment performance.

The significance of network connectedness in finance cannot be overstated, particularly in an era of globalized capital flows and rapid information diffusion. The global financial crisis of 2007-2008 highlighted that the fragility of a financial system is often a function of its interconnectedness rather than the size of its individual components. By conceptualizing the market as a network where nodes represent securities and links represent dependencies - such as correlations, serial predictability, or common borrower relationships - researchers can identify systemic vulnerabilities and diversification opportunities that are invisible to traditional models. This systemic dimension of assets, often quantified through centrality measures, provides a critical lens for understanding how shocks propagate and how investors should optimally allocate wealth to mitigate systemic exposure.

The primary objective of this review is to provide an exhaustive synthesis of recent literature focusing on the intersection of network topology and portfolio optimization. Specifically, it aims to evaluate the various methodologies for network construction, such as Minimum Spanning Trees (MST) and Planar Maximally Filtered Graphs (PMFG), and to analyze the ongoing debate regarding the relationship between asset centrality and optimal weights. Furthermore, the review explores how network-based strategies perform during periods of extreme market stress, such as the COVID-19 pandemic and the Russia-Ukraine War, and how non-financial criteria like Environmental, Social, and Governance (ESG) scores can be integrated into this structural framework.

The scope of this review encompasses a diverse

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range of research settings, including the U.S. S&P 500 and NYSE indices, the UK FTSE 250, the Moroccan Casablanca Stock Exchange, and the Turkish banking sector. It also delves into specialized industry contexts, such as the emerging blockchain market in China. By defining key concepts like eigenvector centrality, network intensity, and interdependency links, the review provides a clear theoretical map for both academic researchers and professional practitioners. The paper proceeds from methodological foundations to thematic findings, concluding with an assessment of existing gaps and future research directions.

2. Methods

The methodology for this review was designed to ensure a rigorous and exhaustive evaluation of the literature that specifically addresses the bridge between complex network analysis and asset pricing models. The search strategy was focused on identifying peer-reviewed studies published between 2013 and 2025 that provide quantitative or theoretical evidence of network application in portfolio selection. Primary databases consulted included the Journal of Empirical Finance, the Journal of Banking and Finance, Quantitative Finance, and specialized outlets for economic modeling and statistical mechanics. Keywords used in the selection process included "eigenvector centrality," "portfolio selection," "interconnectedness," "minimum spanning tree," and "systemic risk."

The inclusion criteria were strictly limited to research that offers a concrete application of graph theory to the Markowitz framework or its derivatives. Studies that were purely descriptive of market structure without proposing an optimization strategy were excluded. The screening process involved a detailed assessment of each paper's methodology for network filtering, as the reduction of information from a fully connected correlation matrix is a critical step in financial network analysis. Special attention was given to papers that utilized long-run correlation estimators, vector autoregression (VAR) for serial dependency, and spatial econometric techniques to measure network intensity.

To assess the quality and robustness of the studies, the review focused on the presence of both in-sample and out-of-sample evaluations, the consideration of transaction costs and turnover rates, and the use of statistical benchmarks like the 1/N (equally-weighted) rule or constrained Markowitz models. The review also evaluated the software and algorithmic tools mentioned in the literature, including Pajek for network visualization and Python-based algorithms for multi-objective optimization like Sequential Least Squares Quadratic Programming (SLSQP) and Particle Swarm Optimization (PSO). This systematic approach ensures that the findings synthesized in Section 4 represent the most methodologically sound and theoretically innovative contributions to the field.

3. Theoretical background

The integration of network theory into portfolio optimization is built upon two distinct yet complementary pillars: Modern Portfolio Theory (MPT) and Social Network Analysis (SNA). This section explores the evolution of these concepts and the theoretical debates that have emerged from their convergence.

3.1. Foundations of asset pricing and diversification

Markowitz (1952) laid the foundation of modern finance by establishing that investors seek to optimize wealth allocation considering only the first two moments of the return distribution: the mean and the variance. In this static framework, the benefit of diversification is derived from the non-perfect correlation between assets. Mathematically, the optimal mean-variance (mv) portfolio weights w_{mv} are derived by minimizing $\sigma^2_p = w^T \sum w$ subject to a target portfolio return R^e , where $\sum$ is the covariance matrix. The resulting weights are given by:

$$w_{mv} = \frac{R^e \Sigma^{-1} \mu^e}{(\mu^e)^T \Sigma^{-1} \mu^e}$$

where μ^e is the vector of expected excess returns. Despite the elegance of this solution, researchers have documented a poor out-of-sample performance due to large estimation errors in μ^e and $\sum$, leading to the "error-maximization" problem where weights are over-allocated to assets with high estimated returns or low estimated variances, which often reflect noise rather than fundamental value.

3.2. Structural representation of financial markets

The transition to a network-based perspective involves redefining the financial market as an undirected or directed graph $G = \{N, \Omega\}$, where nodes N represent individual securities or asset classes and the adjacency matrix Ω accounts for the intensity of interactions. The most common interaction measure is the Pearson correlation coefficient, which, when transformed into a distance metric:

$$d_{ij} = \sqrt{2\left(1 - \rho_{ij}\right)}$$

Allows for the application of topological filtering techniques like MST and PMFG.

The core theoretical innovation in this field is the conceptualization of an asset's systemic dimension. Peralta and Zareei (2016) were the first to theoretically prove a negative relationship between the centrality of an asset in a correlation-based network and its optimal weight in a Markowitz portfolio. The intuition is that highly central nodes are strongly embedded in the network structure; their inclusion in a portfolio undermines the benefits of diversification because their returns are synchronized with a large number of other assets, thereby increasing portfolio variance. This establishes a bridge between the network theory concept of influence and the financial concept of systematic risk, with studies showing a strong positive correlation between network centrality and the CAPM beta.

3.3. Interdependency and the star network paradox

While correlation-based networks capture contemporaneous relationships, they often overlook the dynamic propagation of shocks. Zareei (2019) introduced the interdependency network based on return cross-predictability, modeled through a vector autoregression (VAR) framework. In this model, the links represent serial dependencies, identifying which assets "lead" others in the market. A significant finding is that many financial systems, including international stock markets and industrial sectors, resemble "star-like" structures where a few central nodes cross-affect the rest of the portfolio.

Theoretical results in these star-like structures suggest a failure of the Law of large numbers. In standard diversification, risk converges to zero at a rate of 1/N as more assets are added. However, in an asymmetric star network, the volatility of the portfolio becomes "lower-bounded" by the shock-propagation effect of the central node. This implies that even an infinitely diversified portfolio cannot eliminate the risk originating from a dominant central asset, necessitating a specialized approach to asset selection that avoids these "super-spreaders" of risk.

3.4. Resource-based view and contradictory evidence

A significant theoretical controversy has emerged with the application of the Resource-Based View (RBV) to emerging digital industries. Wernerfelt (1984) proposed that a firm's survival depends on its unique resources and capabilities. Lan et al. (2025) applied this to the blockchain industry, arguing that centrally located firms possess superior access to innovation and market intelligence. Unlike mature industries where centrality is a liability, in high-volatility, innovation-driven sectors, being at the "core" of the network signals competitive advantage and stability. This challenges the universal prescription of peripheral investment, suggesting that the optimal structural strategy is contingent on the industry's maturity and the nature of the resources shared across links.

Authors	Research Setting	Object of the Study	Methodology	Main Findings	Possible limitations and further research
Peralta & Zareei (2016)	US S&P 500 (200 stocks)	Bridge MPT and Network theory; -dependent strategy	Eigenvector Centrality; Panel regression	Negative correlation between centrality and weights; Network strategy beats equally-weighted strategy.	Determination of threshold involves ad-hoc rules
Pozzi et al. (2013)	AMEX (300 stocks, 1981-2010)	Structural spread of risk; Diversification	MST and PMFG; Hybrid centrality indices	Investing in peripheries reduces risk and improves signal-to-noise ratio	Central nodes are persistent; peripheral nodes have high variability
Zareei (2019)	US Industries; Int'l Stock Markets (1980-2014)	Shock propagation and portfolio risk horizons	VAR interdependency network; Katz-Bonacich Centrality	Star-like structures increase risk; Law of Large Numbers fails in asymmetric networks	Conclusions based on serial dependency as primary shock channel
Výrost et al. (2018)	45 Multi-asset classes (Stocks, Bonds, Commodities)	Centrality-based allocation constraints	MST, PMFG, Threshold graphs; Expected Force centrality	Network constraints improve risk and left-tail risk-adjusted returns	Return maximization gains are mitigated by higher transaction costs
Olmo (2021)	FTSE 100 Index; US Volatility/ Financial Indexes	Positive and negative eigenvector centrality	Spectral decomposition of correlation matrix	No universal monotonic relationship between centrality and optimal weights	Focused on Global Minimum Variance; results vary with expected returns
Lan et al. (2025)	Chinese Blockchain Industry (82 companies, 2017-23)	Asset allocation in digital markets (RBV)	Multilayer synthetic network; PSO-PKPS model	Central firms outperform peripheral ones in innovation-driven digital markets	Results may not generalize to mature, non-digital industries
Wang et al. (2024)	86 Multi-asset classes (inc. Crypto & Bond indices)	Centrality comparison during global crises	6 centrality measures (Degree, Eigen, PageRank, etc.)	Hybrid, Eigen, and PageRank are best; Periphery assets better during crises	Specific pool of 86 assets; pool size may bias relative rankings
Bozkurt & Özyıldırım (2025)	Turkish Banking System (44M commercial loans)	Bank connectedness and portfolio riskiness	Bipartite bank-loan network; Weighted degree centrality	Connectedness reduces overall portfolio risk despite higher default probability of borrowers	Findings dependent on Turkish loan concentration structure
El Rhiouane et al. (2025)	Casablanca Stock Exchange (Morocco)	Integrating ESG into network optimization	Markowitz MV; MST; ESG-constrained MV model	RPs not more profitable generally; peripheral portfolios show extreme risk/ reward	Social orientation crisis results in unfavorable outcomes; agency disagreement
Dungey et al. (2022)	45 Economies (Advanced & Emerging, 1998-2018)	Network exposure and dynamic shock transmission	Spatial econometric estimation; SAR framework	Network intensity increases during stress/crises; interconnectedness acts as double edge	Isolation of common factors is complex under global integration

4. Review of findings

The following analysis categorizes the literature into four critical themes: methodological innovations in filtering, the centrality-weight debate, shock propagation and systemic stress, and the integration of technological and ethical variables.

4.1. Methodological innovations in network construction

A primary concern in the literature is how to effectively filter the noise from financial data to uncover the significant dependency structure. A fully connected correlation matrix of N assets yields (N(N-1))/2 links, many of which may be spurious or representative of short-term noise.

4.1.1. Filtering structures: MST versus PMFG

The Minimum Spanning Tree (MST) approach, popularized by Mantegna (1999), reduces the complexity of the market to its skeleton by retaining only edges that maximize correlation while ensuring a connected, acyclic graph. While MST excels at revealing hierarchical clusters (e.g., industry sectors), it may discard important cyclical information. To resolve this, researchers often employ the Planar Maximally Filtered Graph (PMFG), which allows for cycles and retains 3(N-2) edges. Pozzi et al. (2013) demonstrated that PMFG-based selection consistently identifies peripheral stocks that improve the "signal-to-noise" ratio of portfolios compared to central nodes.

4.1.2. Multilayer and synthetic networks

Recent studies have moved beyond single correlation measures toward multilayer constructions. Lan et al. (2025) introduced the PSO-PKPS model, which synthesizes Pearson, Kendall tau, Partial, and Spearman correlations into a single optimized network using Particle Swarm Optimization. This methodology allows for the capturing of both linear and non-linear dependencies simultaneously. The PSO algorithm searches for the optimal weights to combine different correlation layers, ensuring that the resulting structural map has the highest informational content regarding stock returns.

4.1.3. Bipartite and projected networks in banking

In specialized sectors like banking, the network structure is often bipartite, consisting of two distinct sets of nodes (e.g., banks and firms). Bozkurt and Özyıldırım (2025) utilized over 44 million loans to construct a bipartite network where edges exist only between banks and borrowers. By projecting this into a one-mode bank network based on common firms, they proposed a new weighted degree centrality that accounts for the volume of loans shared between institutions. This approach reveals how "common asset holdings" create indirect interconnections that traditional interbank lending models fail to capture.

4.2. The core-periphery debate in asset selection

The relationship between an asset's network position and its optimal portfolio weight remains the most debated topic in the field, with findings divided by market maturity and industry type.

4.2.1. The case for peripheral diversification

The established consensus in mature markets is that investors benefit from underweighting central assets. Peralta and Zareei (2016) proved that highly central securities in a correlation network undermine diversification because they are systemic risk carriers. This is corroborated by Pozzi et al. (2013), who found that peripheral stocks - those in poorly connected regions of the PMFG - exhibit larger average yearly excess returns and superior anti-cyclic patterns compared to central ones.

During global crises, such as the COVID-19 pandemic, this "periphery advantage" becomes even more pronounced. Wang et al. (2024) analyzed 86 multi-asset classes and found that peripheral assets, particularly those from emerging countries, are less exposed to external shocks and more likely to remain stable during systemic collapses. In these environments, centrality is synonymous with vulnerability to contagion.

4.2.2. The case for central concentration in digital industries

Conversely, research into innovation-driven sectors like blockchain presents a counter-intuitive finding. Lan et al. (2025) found that in China's blockchain industry, investing in peripheral firms failed to yield positive cumulative returns or positive Sharpe ratios. Instead, central firms, which are "resource-rich" and have better access to external knowledge, consistently outperformed. This suggests that in rapidly evolving industries, a structural position at the "core" is a signal of quality rather than a risk exposure.

Furthermore, Lan et al. (2025) introduced the "return dilution" argument, stating that while "eggs should not be placed in one basket," they also should not be scattered into too many peripheral baskets. Excessive diversification in these markets dilutes the potential gains from core, high-performing innovators without providing a commensurate reduction in risk.

4.2.3. Positive and negative centrality

Olmo (2021) provided a mathematical correction to the centrality-weight relationship. He argued that the standard Bonacich centrality is misleading because it assumes that the adjacency matrix (built upon asset returns' correlations) contains only positive values. In reality, negative correlations between financial indexes and volatility indexes (like the VIX) can cause standard centrality scores to cancel out, making an asset appear peripheral when it is actually a highly connected hedge. The author proposed separate "positive" and "negative" centrality measures and showed that a monotonic relationship between centrality and risk only holds under short-selling constraints and is not a universal law of financial networks.

4.3. Risk propagation and systemic connectivity

The network structure is a dynamic entity that undergoes significant transformations during periods of market stress.

4.3.1. Robust-yet-fragile systems

Dungey et al. (2022) characterized global financial networks as "robust-yet-fragile". Under normal conditions, high connectivity facilitates risk-sharing and shock absorption. However, once a certain threshold of "network intensity" is reached, the network becomes a conduit for rapid contagion. Spatial econometric modeling shows that network intensity coefficients (the strength of unit interactions) spike during extreme events like the Global Financial Crisis and the 2015 Chinese stock market crash. This suggests that policy makers should focus on monitoring the "Too Interconnected To Fail" (TITF) paradigm rather than just institution size.

4.3.2. Shock horizons: Katz-Bonacich centrality

Zareei (2019) distinguished between short-term and long-term risk using two different centrality measures. Threatening-degree centrality captures the influence of a shock one period ahead, whereas Katz-Bonacich centrality captures the cumulative, long-term effect by accounting for higher-order connections (shocks spreading from node A to B and then to C). Empirical evidence from U.S. industries shows that the financial sector acts as the central hub of a star network, and during the 2007-2008 crisis, the percentage of portfolio volatility stemming from this interdependency network surged to 24% of the total risk.

4.3.3. Bank resilience through connectivity

In the Turkish banking system, Bozkurt and Özyıldırım (2025) found a seeming paradox: while firms that borrow from multiple banks are individually more prone to default, the banks that are most connected to these common firms actually manage their overall portfolio risk better. This suggests that "highly centralized banks" might have better incentives to monitor common borrowers or have developed structural resilience that allows them to absorb individual defaults without affecting the integrity of their entire loan portfolio.

4.4. Technological Integration and ESG Constraints

Modern portfolio optimization must now contend with ethical considerations and the rise of digital asset classes like cryptocurrencies.

4.4.1. ESG and network frontiers

Integrating Environmental, Social, and Governance (ESG) criteria into a network framework represents a new frontier. El Rhiouane et al. (2025) developed an MV-ESG model for the Moroccan market, imposing a minimum acceptable threshold for ESG scores as a constraint in the Markowitz optimization. They found that while responsible portfolios are generally neither more profitable nor less volatile than conventional ones, the use of MST networks identified better opportunities for returns in post-crisis periods. However, they warned that focusing on social issues during a social orientation crisis such as a pandemic can eliminate the potential for favorable financial outcomes, as the costs of maintaining high ESG scores may impair a firm's financial resilience.

4.4.2. Cryptocurrencies as spillovers

The cryptocurrency market has introduced new dynamics into financial networks. Wang et al. (2024) found that Ether (ETH) has recently replaced Bitcoin (BTC) as the "number one network transmission cryptocurrency," showing the highest centrality in cross-market networks. This suggests that ETH now acts as a primary conduit for sentiment and risk shocks within the digital asset class, a fact that optimization models must account for when building multi-asset portfolios including both traditional and crypto assets.

4.4.3. Portfolio combination strategies

To address model selection uncertainty, Výrost et al. (2019) recommended combination portfolios that invest 50% in a benchmark (like a return-maximization portfolio) and 50% in network-based strategies. They found that this approach consistently improves key metrics like the Burke ratio and left-tail risk-adjusted returns (Expected Shortfall). These improvements remain robust even when accounting for transaction costs, particularly for risk-minimization objectives.

5. Conclusion

The synthesis of literature on network connectedness and portfolio optimization demonstrates that the structural position of an asset within a dependency network is a critical, yet often overlooked, determinant of its contribution to portfolio risk and performance.

5.1. Summary of main findings

The primary consensus across the reviewed studies is that financial markets often exhibit asymmetric, star-like structures where risk propagation is concentrated in central hubs, such as the financial sector or the U.S. stock market. In these environments, the Law of Large Numbers fails, and traditional diversification is insufficient to eliminate systematic structural risk. Most research in mature markets advocates for an allocation strategy that overweights peripheral assets those less connected to the systemic core as a means to enhance risk-adjusted returns and avoid contagion conduits.

However, the periphery advantage is not universal. In emerging digital industries like blockchain, the Resource-Based View suggests that centrality acts as a signal for superior resource access and innovation capability, making central firms more desirable than peripheral ones. Furthermore, the relationship between centrality and risk is highly dependent on the presence of short-selling constraints and the sign of the correlations (positive vs. negative) within the adjacency matrix. Methodologically, advanced filtering techniques like PMFG and multilayer synthetic networks using Particle Swarm Optimization offer the most robust maps of these complex dependencies.

5.2. Identified literature gaps

Despite these advancements, several critical gaps remain. First, there is a lack of consensus on the dynamic identification of threshold parameters for network intensity. While researchers agree that networks transition from shock-absorbent to shock-amplifying, identifying the precise tipping point in real-time remains elusive. Second, while the impact of centrality on the Global Minimum Variance portfolio is well-documented, its interaction with the mean (expected returns) component of mean-variance strategies is still theoretically underdeveloped. Third, the divergence in ESG ratings across different agencies (Refinitiv vs. MSCI) complicates the construction of network-based responsible portfolios, as an asset's centrality may change based on the ESG data provider used.

5.3. Future research directions

Future research should focus on the development of dynamic threshold rules for the -dependent strategy, allowing investors to switch between core and peripheral focus as market conditions evolve from stability to crisis. There is also a significant need to test the Resource-Based View of network centrality in other high-tech sectors, such as artificial intelligence and green energy, to see if the "centrality-over-periphery" advantage holds in all innovation-driven digital markets.

Furthermore, future studies could explore the application of tensor decomposition and other high-dimensional techniques to extract structural relationships from heterogeneous data sources beyond simple price time series. Finally, the integration of regulatory constraints and liquidity factors into the centrality-weight relationship would move the theoretical network findings closer to actual practical investment applications. By bridging these gaps, the field can advance toward a truly structural theory of asset allocation that accounts for the multifaceted nature of global financial interconnectedness.

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