Portfolio Optimization with Graph Representation

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***Abstract*—This piece of work investigates the importance that Graph Representation and Clustering algorithms have on addressing the systemic risk and complexity that comes with modern investment portfolios [6], [7]. Traditional mean-variance models provided by most institutions prove to be quite inadequate as they fail to capture the surrounding dependencies and time varying contagion networks that characterize Big Data in finance.**

The key contribution across all of these studies is the shift in correlation matrices towards something more complex like network topology to assess risk [5]. Many Graph theoretic frameworks are applied to two primary challenges in finance, diversification and contagion risk mitigation.

1) **Diversification: The authors in most of the articles employ techniques like Planar Maximally Filtered Graphs (PMFG) and Spectral Clustering to map assets into stable communities called cliques [3], [4]. This will allow investors to achieve true diversification by choosing assets from a multitude of clusters, rather than relying on a nominal sector of separation [5], [8].**
2) **Contagion Risk Mitigation: Graph analysis is used to directly quantify systemic fragility. This is achieved through the definition of node influence through the Stock Centrality and Weight of edges that accompany unique metrics like Conditional Value at Risk ($\triangle CoVar$) [1]. It can also be achieved by creating an economic link that is based on Transaction Cost Thresholds to map the global market integration [2].**

While the graph-based approaches offer a more intelligent way to interpret and structure these risk insights, the implementation faces Big Data Challenges, including the high computational cost of advanced metrics ($\Delta CoVar$) and the necessity that it brings to building dynamic, time-varying graphs to track multiple relationships in an effective manner [4]. Any future research done on this topic must focus on integrating these models utilizing distributed computation like MapReduce and machine learning like Graph Neural Networks. Future work must apply these models with their specifications to ensure a real-time adapation is available, and scalability is possible across vast and volatile global markets.

***Index Terms*—Graph Representation, Portfolio Optimization, Systemic Risk, Financial Contagion, Clustering Algorithms, Conditional Value-at-Risk ($\Delta CoVaR$), Network Topology, Stock Centrality, Big Data Analytics, Market Diversification**

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I. Introduction

The growing popularity and rise of high-frequency trading, interconnectedness of global markets, and the exponential growth of available data create a fundamental shift in the way that investment portfolios are managed and risk is assessed. The entire environment of modernity in finance is profiled by an unprecedented scale and velocity, which presents many significant challenges for traditional analytical tools [6]. The challenges fall under the known domain of **Big Data Analysis**, which demands for methods that are capable of handling a large volume, velocity, and extreme complexity.

The Limits of Traditional Risk Models

For a while, the construction of portfolios has been founded by the principles of Markowitz, which primarily relies on the variance covariance matrix to measure risk. This methodology, although runs under a few key assumptions, like the normality of returns that consistently fails during periods when the market is under extreme stress. The most crucial failure would be the inability to accurately capture **contagion** and **systemic risk**. When there is a crisis, assets that appear uncorrelated suddenly coincide one another, leading to many catastrophic losses [1]. This now becomes a phenomenon that simple linear models struggle to predict or explain. Furthermore, traditional models has a hard time with **high-dimensional data** that is associated with a multitude of potential assets and complicated exposures.

Graph Representation: A Foundational Solution

To overcome the predefined structural limitations, there has been academic and industry research that increasingly moved towards a network based paradigm, which utilizes **Graph Representation** as the core data method that runs through the stack. This unique approach makes the financial market out to be a living network, where the assets and the nodes and functional dependencies between them are edges [7]. The change in measuring correlation in a simple matrix to modeling the topology allows the methodology to discover hidden structural dependencies that drive the risk between stocks and opportunity [5]. This research paper reviews the effectiveness of the Graph Theoretic frameworks and the related **Clustering Algorithms** when addressing the most challenging obstacles in quantitative finance: **Diversification** and **Contagion Risk Mitigation**.

A. Diversification through Structural Clustering

The goal of diversification is to reduce the likelihood of assets to fall together. To employ this methodology, researchers have applied graph filtering and clustering techniques that will allow them to identify natural structural groupings within the market:

1) **Filtering and Clustering Graphs:** Techniques like **Minimum Spanning Trees (MST)** and the more advanced technique the **Planar Maximally Filterd Graph (PMFG)**, are used to refine the thousands of noisy correlations down to only the most significant and essential relationships in the topology.
2) **Community Detection:** Algorithms like **Spectral Clustering** and **Infomap** are used to these distilled graphs to split assets into stable communities or cliques [3], [4]. This structural division proves that assets that are in the same community are highly interdependent, that will guide investors to choose assets from different communities to construct a well risk adverse portfolios.

B. Systemic Risk and Contagion Modeling

Beyond the simple grouping that occurs, the graph representation aspect allows for direct quantification of systemic risk, which is very important during tail risk events.

1) **Tail Risk Quantification:** The crucial metric named **Conditional Value at Risk** ($\Delta Covar$) is calculated between two assets, known as nodes in the graph model. This calculation is used to put a value towards the specific marginal contribution of an asset's failure to the overall stress of the entire topology [1]. This calculated metric is then used to weight all the edges in the graph, turning the entire network into a graph like structure.
2) **Centrality Analysis:** Once the nodes are weighed by ($\Delta Covar$), the network is then put through analysis using **Stock Centrality** metrics (like Eigenvector Centrality). These calculations identify the "kingpin" assets whose failure would cause all the other stocks to fail with it. By reducing the amount of stocks and assets that are exposed to these high-centrality assets, portfolio managers will be able to mitigate the contagion risk [1].
3) **Global Integration Risk:** Furthermore, the methodology of these concepts extend beyond the domain of security prices. Lillo and Valdes showed that by establishing links based on economic relations, specifically **Transaction Cost Thresholds**, the graph then can map the entire structural flow of capital, which indicates highly integrated global market cliques that share similar systemic risk [2].

C. Conclusion and Future Directions

All of these findings strengthen the notion that graph-based models have a superior interpret-ability and analytical power when confronting financial complexity. Although this is true the application of this methodology begs significant **Big Data Challenges**. Building **dynamic, time-varying graphs** then becomes a necessity to track the constantly shifting relationships throughout the market. Additionally, the market demands heavy computational resources and as byproduct will require any future research to focus on this area [4]. Furthermore, any steps to progress this study must concentrate on integrating graph algorithms with **distributed computing frameworks** (like MapReduce) and supplementary **Machine learning techniques** (e.g, Graph Neural Networks) to capture the required processing speed and scalability that is necessary for an adaptive, real-time management of risk across many volatile global markets.

II. Literature Review

A. Dynamic Portfolio Cuts (Arroyo et al., 2021)

The rise of graph-theoretic finance has emerged as a response to the limitations of classical mean–variance optimization, particularly the assumption of static covariance structures. Financial markets evolve dynamically, and diversification strategies must adapt accordingly. *Dynamic Portfolio Cuts: A Spectral Approach to Graph-Theoretic Diversification* [4] presents a methodology that models asset relationships using time-varying spectral graphs. This review analyzes the paper's contributions, evaluates its methodological strengths and weaknesses, and explains its relevance to our research on graph-based risk mitigation. The goal is not only to summarize the work, but to interpret its findings within the broader context of systemic risk modeling.

Arroyo et al. argue that traditional covariance estimation cannot track market regime changes, shocks, or contagion events. Their proposed framework replaces static dependency structures with a **dynamic spectral covariance estimator** that updates graph topology over time. Instead of allocating capital through mean–variance optimization, they use spectral methods to segment assets into evolving clusters, enabling diversification that reflects real-time market structure fluctuations. This shift toward time-sensitive graph analysis aligns closely with the direction of our research, which similarly examines network topology as a tool for market stress interpretation.

The authors construct market graphs using rolling-window spectral decomposition, generating a *dynamic Laplacian* whose eigenvectors reflect shifting relationships among assets. Cluster formation occurs through Fiedler vector partitioning, producing **Dynamic Spectral Portfolio Cuts** that evolve as correlations change. Backtesting on S&P500 and commodity futures demonstrates that spectral diversification outperforms both static graph-based allocation and traditional Markowitz portfolios in cumulative return and Sharpe ratio.

Key takeaways from Dynamic Portfolio Cuts include:

- Dynamic Laplacian estimation enables tracking of evolving dependency structure.
- Spectral clustering reallocates capital when graph topology shifts.
- Out-of-sample testing confirms practical viability and real-world applicability.

A key strength of this work is its departure from static assumptions. The paper demonstrates that diversification must reflect nonstationary market behavior, and spectral cuts offer a scalable method to achieve that. It also avoids covariance inversion, reducing instability under high dimensionality, a weakness of classical MPT. However, limitations exist. First, the computational load increases significantly as graph-update frequency rises. Second, while the model adapts clusters over time, it does *not* explicitly measure systemic contagion or node influence. Unlike Network Risk Parity models, it lacks centrality weighting and ΔCoVaR propagation metrics. These gaps directly motivate our research expansion.

This paper provides a foundational argument for using graph based frameworks in portfolio construction. Its dynamic spectral clustering method demonstrates that evolving topology represents market structure more accurately than static variance–covariance matrices. This contribution supports our work by validating the need for network-aware diversification models. At the same time, its limitations particularly the absence of contagion and centrality risk quantification—define a clear research gap. Our project extends this trajectory by integrating systemic–risk measures and high-frequency network expansion, advancing toward a model capable of real-time fragility detection and contagion mitigation.

B. Network Risk Parity

Modern portfolio construction has shifted away from classical covariance-based optimization toward graph-theoretic models that better capture systemic market structure. One recent contribution within this movement is the *Network Risk Parity* framework [9], which proposes a network-driven approach to allocation based on eigenvector centrality and Minimum Spanning Trees (MST). This literature review examines that work in depth, synthesizes its findings, and evaluates its relevance for our research on graph-based diversification and contagion modelling. Unlike a summary, this review highlights methodological strengths, theoretical contributions, and limitations that inform the direction of our own study.

Network Risk Parity (NRP) emerges as a refinement to Hierarchical Risk Parity (HRP), addressing the fact that HRP only considers one-to-one asset relationships within a tree, ignoring the broader network influence structure. NRP instead constructs a Minimum Spanning Tree from the correlation network and then weights assets inversely to their eigenvector centrality, reducing exposure to highly influential hubs. This graph-based technique does not require matrix inversion, avoids concentrated portfolios, and maintains positive weights across assets, unlike Markowitz optimization which often collapses into sparse allocations. The paper's bootstrapped results (2010–2023) show that NRP outperforms HRP, Mean-Variance, and Equal-Weight portfolios in Sharpe ratio across large universes, especially as dimensionality increases.

The significance of this work lies not just in performance gains, but in how it reframes diversification. Traditional approaches seek risk reduction through variance minimization, assuming stable correlations; NRP instead measures risk through *topological influence*. The use of eigenvector centrality acknowledges that contagion is nonlinear — distress spreads through hubs, not evenly across all assets. In this way, NRP aligns with a systemic perspective rather than a statistical one. This interpretation is especially important because it demonstrates a pathway for graph-based models to outperform classical finance by recognizing market structure as a network, not a matrix.

Critical Evaluation Strengths of the work include theoretical clarity, mathematical justification for positive-weight diversification, and empirical validation across multi-year S&P 500 data. Its reliance on MST filtering also reduces noise, similar to the filtering stage in spectral graph frameworks. However, a limitation is that the model remains *static*: the MST topology and centrality scores do not evolve through time. As a result, the portfolio does not adapt to changing contagion conditions or regime shifts. While superior to covariance inversion, NRP does not fully capture *dynamic systemic risk* a gap our current research aims to address by shifting towards time varying network construction and spectral clustering techniques.

The Network Risk Parity paper is relevant not merely as supporting literature but as a foundational argument for viewing portfolios as networks rather than covariance matrices. It demonstrates that diversification improves when assets are selected based on graph structure and influence pathways rather than linear correlations alone. Most importantly, its limitation static topology, no temporal evolution directly motivates our research question. Our work extends this direction by incorporating dynamic graph representations and contagion modelling, aiming to achieve real-time systemic risk awareness rather than fixed network allocation.

C. Literature Review — Asset Trees and Asset Graphs (Onnela et al., 2003)

The article by Onnela et al [7]. presents one of the foundational approaches to understanding financial markets using graph representations. The authors address a major issue with traditional financial data analysis: correlation matrices become overwhelmingly large, dense, and noisy as the number of assets increases. Because most stocks exhibit some degree of correlation with many others, the raw correlation matrix does not clearly reveal meaningful structure. This makes it difficult to identify which relationships are genuinely important and which are simply statistical noise.

To solve this problem, the authors propose transforming the correlation matrix into a distance metric and then applying graph-based filtering techniques. Two main structures are introduced: the Minimum Spanning Tree (MST) and the Asset Graph. The MST connects all stocks while keeping only the most essential edges, effectively removing redundant information. This produces a "skeleton" of the market where only the strongest and most meaningful relationships remain. The Asset Graph further filters the network by applying correlation thresholds so that only edges above a certain significance level are retained. While the MST guarantees connectivity, the Asset Graph is allowed to produce disconnected clusters, revealing natural groupings within the market.

One of the key insights from the article is that financial markets tend to organize themselves into community-like clusters, where groups of assets often from related industries form tightly connected components. This result highlights how network filtering can expose economic structure that is hidden within the full correlation matrix. The authors show that these simplified graph representations allow analysts to study market behavior during different periods and detect changes in structure caused by market events.

Despite its contributions, the approach has limitations. First, it relies only on linear correlation, which may not capture nonlinear or higher-order relationships among assets. Second, graph construction requires choosing thresholds or filtering rules, which introduces subjectivity and may affect the network outcome. Finally, reducing the network to an MST removes cycles and therefore eliminates potentially informative redundant connections. Nonetheless, the article remains an important contribution and forms the basis of many later graph-based market analysis techniques.

D. MST-Based Portfolio Optimization (Berouaga et al., 2023)

This article takes graph-theoretic concepts beyond market structure analysis and applies them directly to portfolio optimization. Traditional portfolio models, such as Markowitz's mean-variance framework, often struggle in real-world financial environments especially in emerging markets, because they rely heavily on covariance matrix estimation. When the data is noisy or limited, these covariance estimates become unstable, resulting in unreliable portfolio weights [8].

Berouaga et al. address this issue by constructing a Minimum Spanning Tree (MST) from stock return data in the Moroccan stock market. In the MST, each stock's connectivity reflects how strongly it is related to the rest of the market. Highly connected stocks tend to move in sync with many others, while peripheral stocks exhibit more unique behavior. The authors leverage this structure to select assets that improve diversification and reduce portfolio risk. Specifically, they favor stocks with lower degree centrality those located on the edges of the MST because these assets contribute more independent information to the portfolio.

The authors then build MST-based portfolios and compare their performance to traditional benchmarks including the Markowitz model and equal-weight strategies. Their results show that MST portfolios achieve competitive, and sometimes superior, performance while maintaining lower volatility and greater stability. The method is computationally simple and avoids many of the statistical challenges that arise from estimating full covariance matrices.

However, the approach also has limitations. Since the MST removes all cycles, it oversimplifies the true structure of the financial network and may ignore important secondary relationships. The model was tested only in the Moroccan market, so the results may not generalize across different regions or market conditions. Additionally, because the approach relies on historical return windows, it may respond slowly to sudden structural changes in the market. Even with these limitations, the article demonstrates how network analysis can offer viable alternatives to classical financial optimization techniques.

E. Portfolio Cuts: A Graph-Theoretic Framework to Diversification

When constructing an optimal investment portfolio, we ideally want a collection of assets that is diversified, exhibits low overall risk, and still offers the potential for high returns. Traditional portfolio optimization approaches most notably the Markowitz mean–variance model represent a portfolio as a vector of asset weights and use a correlation matrix to capture similarity between assets. This matrix is used to promote diversification such that if assets are strongly correlated, the optimizer will typically avoid allocating weight to both. However, these correlations are purely statistical, based entirely on historical returns. As a result, the correlation matrix may fail to reflect our actual understanding of how assets are related in the real economy. For example, it is possible for a mean–variance optimizer to place most of the weight in companies like NVDA, TSLA, AAPL, and MSFT, all tech companies. Although these firms have similar economic statuses, their correlations may not be high enough for the algorithm to view them as similar. Hence, the algorithm may regard this collection as diversified when we don;t. While these algorithms account for risk and return, they often neglect true economic diversification and may concentrate heavily in only a small number of related assets. As the authors note, such portfolios "typically yield results that are far from truly optimal ones; these may even exhibit poor performance and excessive turnover" [[5], Ch. 1, p. 1]. In their paper, the authors address this problem by proposing a framework that incorporates domain knowledge directly into the optimization process. Instead of relying on a correlation matrix to measure similarity, they replace it with a matrix that utilizes economic relationships between assets. Relationships are based on industry and sector classifications rather than statistical ones. Using this economic similarity matrix, the optimizer enforces diversification in a way that aligns with our intuitive understanding of how assets are related.

The algorithm assigns similarity values based on their industry and sector. If two assets belong to the same industry, their similarity score increases. If they belong to the same sector, their score also increases. After computing these similarity scores for every pair of assets, we obtain a matrix that captures economic similarity across the entire asset universe. This then becomes the foundational object that guides diversification in the portfolio.

By optimizing with respect to this economic similarity matrix, the resulting portfolios tend to be more balanced across industries and sectors, producing allocations that more closely match what investors typically perceive as diversified. One drawback of replacing the correlation matrix is that the model no longer uses statistical risk. As a result, it may sacrifice some degree of risk in favor of broader diversification. However, we can make an intuitive argument that a diversified portfolio should have a lower overall risk, even if some individual assets are risky. Poor performance in one industry is less likely to affect unrelated industries. Although the portfolio may not explicitly minimize variance in the traditional sense, the diversification enforced by the economic similarity matrix may still yield portfolios with favorable risk characteristics on average.

F. Improving Portfolio Management using Clustering and Particle Swarm Optimisation

Particle Swarm Optimisation (PSO) is a metaheuristic that can serve as an alternative to traditional Mean–Variance Optimization (MVO). Unlike classical optimization methods, PSO is explicitly designed to operate effectively under noisy, high-dimensional, real-world data environments. PSO attempts to determine an optimal allocation of assets by exploring candidate solutions and iteratively adjusting portfolio weights according to objective functions that balance risk and return, such as the Sharpe Ratio. [10]

The intuition behind the technique is often illustrated through the analogy of a flock of birds searching for water in a desert. The birds spread out to explore the landscape; some discover small pools while others encounter large lakes. Each bird uses both its own best discovery and the best discovery made by the group as a whole to determine its direction of movement. Ultimately, the flock is expected to converge toward the largest body of water. Mapping this analogy to the optimization problem, the domain of the function represents the desert, local maxima correspond to individual water sources, and the global maximum represents the largest and most desirable source of water. Instead of birds, PSO uses candidate portfolio asset weights that explore the search space to identify the allocations that maximizes the return to risk ratio.

A key advantage of PSO is that it does not rely on gradient information to locate optimal solutions. Instead, it employs a weighted combination of each asset's personal best value and the global best value observed across all assets. However, this technique comes with limitations. PSO is an iterative algorithm, meaning it converges gradually through repeated updates, which can significantly increase computational time. Additionally, this formula for PSO contains multiple sensitive hyperparameters that require careful tuning to achieve a desirable solution. Even after extensive iterations, convergence to the true global maximum is not guaranteed.

Finally, like many portfolio optimization techniques, PSO is vulnerable to the curse of dimensionality. In practice, restricting the input size to roughly 100 assets or fewer is often necessary to obtain results within a reasonable computational timeframe.

G. Optimal Portfolio Choice and Stock Centrality for Tail Risk Events

The analysis of financial markets increasingly relies on complicated data mining techniques to combat the deficiencies of investment portfolio theory particularly concerning risk modeling during periods of crisis. Two notable studies exemplify this methodology by leveraging graph representation to quantify the complexities around the market.

Christis Katsouris's work, Optimal Portfolio Choice and Stock Centrality for Tail Risk Events [1], provides a crucial framework for managing systemic risk. The primary advantage of this approach lies in its ability to directly model contagion by replacing the traditional covariance matrix with one based on the Δ CoVaR metric. This allows for a measurement of an asset's marginal contribution to the overall system's distress during extreme events. The subsequent use of Stock Centrality algorithms identifies the most structurally influential assets, providing clear guidance for mitigating the network risks. However, this methodological hardship introduces complexity. A significant disadvantage is that the inherent computational intensity of quantile regression required to derive ΔCoVaR, posing a great challenge to implementation and real time processing due to the high volume and velocity of financial data. Furthermore, the model's reliance on accurate estimation introduces vulnerability to measurement error.

H. Dynamics of financial markets and transaction costs: A graph-based study

Felipe Lillo and Rodrigo Valdés, in Dynamics of financial markets and transaction costs: A graph-based study [2], offer a powerful mechanism for understanding global market integration. The study's chief advantage is its foundation in economic interpretability . Instead of relying on potentially unstable price correlations, the authors define asset links based on a transaction cost threshold, which serves as a solid proxy for barriers to capital flow. This graph representation reveals hidden cliques effectively, or integrated communities of global markets, providing an accurate measure of integration risk. The application of community detection then clearly maps which markets are structurally vulnerable to mutual destruction. On the other hand, a disadvantage is that the model's reliance on a static threshold for creating the edges. Because the financial dynamics shift frequently, this approach risks quickly becoming obsolete if the threshold is not adapted, failing to capture evolving market conditions. Another limitation is the use of market indices rather than individual stocks, which restricts the model's direct utility for constructing detailed, asset specific investment portfolios.

III. Discussion

The surveyed literature demonstrates a clear progression from classical covariance based allocation toward graph-theoretic financial modeling. Across methods such as Minimum Spanning Trees (MST) [8], Asset Graphs [7], Dynamic Spectral Portfolio Cuts [4], Network Risk Parity [9], and graph-derived diversification matrices [5], a consistent trend emerges: correlations alone are insufficient to represent systemic risk, whereas network topology reveals hidden inter dependencies that traditional models ignore.

Three core insights surface from the literature. First, graph-filtering techniques like MST and PMFG reduce noise and expose latent cluster structure that improves diversification [3], [8]. Second, dynamic spectral clustering adapts to regime shifts by updating topology in real time [4], outperforming static methods in environments where relationships evolve rapidly. Third, systemic fragility can be quantified using measures such as eigenvector centrality and ΔCoVaR, enabling identification of contagion-propagating nodes [1]. Instead of measuring volatility in isolation, these works highlight network influence as a primary driver of risk.

Despite their advantages, tradeoffs remain. MST-reduced networks may oversimplify market structure by discarding cycles [7]. Centrality-based allocation reduces exposure to influential hubs, yet may under-allocate high-momentum assets during bull cycles [9]. Dynamic spectral models capture time variation but incur heavy computational overhead in high-frequency settings [4]. These limitations indicate that graph-based finance is powerful but incomplete further integration of machine learning, streaming data, and distributed graph computation is necessary for real-world scalability.

Collectively, the reviewed research points to a gap that remains insufficiently addressed: few models simultaneously achieve dynamic topology, contagion propagation measurement, and scalable computation. A framework combining these dimensions would represent meaningful progress toward real-time systemic-risk-aware portfolio management.

IV. Conclusion

This paper examined graph-theoretic methods for portfolio optimization and systemic risk modelling, drawing on frameworks such as Portfolio Cuts [5], Network Risk Parity [9], Asset Trees and Graph Filtering [7], and Dynamic Spectral Allocation [4]. The collective findings show that networks capture structural relationships between assets more effectively than covariance matrices, enabling contagion-aware diversification, cluster-based allocation, and improved resilience during tail-risk events [1], [3].

While graph-driven allocation offers interpretability and robustness, future development must prioritize scalability. Real-time markets require time-varying graph construction, centrality-aware contagion modeling, and parallel processing for large asset universes. Promising future directions include graph neural networks, streaming network analytics, and distributed frameworks such as MapReduce to handle Big Data scale efficiently [4], [6].

In summary, graph representation marks a transition from optimizing variance to understanding interconnectedness from minimizing volatility to minimizing systemic fragility. With computational advances accelerating, graph-based risk modeling is positioned to become a foundational component of next-generation portfolio construction and financial stability analysis.

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