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## GRAPH NEURAL NETWORKS FOR SYSTEMATIC RISK AND CLUSTER-BASED DIVERSIFICATION

*The paper presents a study of Graph Neural Networks as a superior alternative to Euclidean-based correlation models for understanding market interconnectedness. Traditional diversification strategies often assume that assets are independent or have linear correlations, failing to account for the complex, non-linear contagion paths in global markets. This study models the stock market as a Dynamic Heterogeneous Graph, where nodes representing assets are connected by edges that signify multiple relationship types, such as supply chain links, common institutional ownership, and lead-lag return correlations. The study proposes a Graph Attention Network architecture to learn Risk Embeddings that quantify an asset's vulnerability to shocks propagating through the network.*

*The purpose of the work is to develop a topology-aware diversification framework that identifies hidden clusters of risk. By using Graph Neural Networks, the research seeks to move beyond sector-based diversification toward a data-driven graph-cluster approach that accounts for the structural complexity of the modern financial ecosystem and its inherent systemic dependencies.*

*The methodology encompasses constructing dynamic asset graphs using thresholding and k-Nearest Neighbors on Pearson and Spearman correlations, deploying Message Passing Neural Networks to aggregate risk signals from neighboring nodes, applying Hierarchical Risk Parity on the learned graph embeddings instead of raw returns, and correlating node centrality with asset beta and tail risk metrics.*

*The scientific novelty. The research introduces the Multi-Relational Risk Embedding, a novel vector representation of assets that captures higher-order dependencies. Unlike linear Principal Component Analysis, this graph-based embedding identifies how a shock to a specific node flows through the network to affect distant nodes, providing a predictive measure of systemic fragility based on the topology of the financial system.*

*The practical value lies in offering risk managers a stress-test visualization tool that identifies super-spreader assets within a portfolio. It enables the construction of anti-fragile portfolios that are structurally decoupled, reducing the likelihood of simultaneous collapses during liquidity crises and providing a more granular view of diversification.*

*Conclusions. Network topology is a critical dimension of market risk that is often ignored by classical models. The study finds that graph-informed clustering identifies risk concentrations that traditional methods miss, leading to a significant improvement in the Sortino ratio and a substantial reduction in maximum drawdown during periods of market contagion.*

*Key words: Graph Neural Networks; Systemic Risk; Portfolio Diversification; Financial Topology; Message Passing; Hierarchical Risk Parity; Contagion Modeling*

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## ГРАФОВІ НЕЙРОННІ МЕРЕЖІ ДЛЯ СИСТЕМНОГО РИЗИКУ ТА КЛАСТЕРНО-ОРІЄНТОВАНОЇ ДИВЕРСИФІКАЦІЇ

*У статті представлено дослідження графових нейронних мереж як більш досконалої альтернативи кореляційним моделям, заснованим на евклідовій геометрії, для аналізу взаємозв'язків на фінансових ринках. Традиційні стратегії диверсифікації часто ґрунтуються на припущенні про незалежність активів або наявність між ними лише лінійних кореляцій, що не враховує складні нелінійні шляхи поширення шоків у глобальних ринках. У роботі фондовий ринок моделюється як динамічний гетерогенний граф, у якому вузли, що представляють активи, з'єднані ребрами, які відображають різні типи взаємозв'язків, зокрема виробничі ланцюги постачання, спільну інституційну власність та лагові кореляції дохідностей. Запропоновано архітектуру Graph Attention Network для формування ризикових вкладень (Risk Embeddings), які кількісно оцінюють вразливість активу до шоків, що поширюються мережею.*

*Метою роботи є розроблення топологічно орієнтованої моделі диверсифікації, здатної виявляти приховані кластери ризику. Використання графових нейронних мереж дозволяє перейти від галузевої диверсифікації до підходу, заснованого на кластеризації графа за даними, що враховує структурну складність сучасної фінансової екосистеми та притаманні їй системні залежності.*

*Методологія передбачає побудову динамічних графів активів із використанням порогової фільтрації та алгоритму k-найближчих сусідів на основі коефіцієнтів кореляції Пірсона та Спірмена, застосування Message Passing Neural Networks для агрегування ризикових сигналів від сусідніх вузлів, використання підходу Hierarchical Risk Parity до навчених графових вкладень замість безпосередніх рядів дохідностей, а також аналіз зв'язку між центральністю вузлів і показниками бета-коефіцієнта та хвостового ризику.*

*Наукова новизна полягає у впровадженні багатовимірного ризикового вкладення (Multi-Relational Risk Embedding) — нового векторного представлення активів, що враховує залежності вищого порядку. На відміну від лінійного методу головних компонент, запропоноване графове вкладення дозволяє простежити, як шок у конкретному вузлі поширюється мережею та впливає на віддалені вузли, формуючи прогностичну оцінку системної крихкості на основі топології фінансової системи.*

*Практична цінність дослідження полягає у створенні інструменту візуалізації для стрес-тестування, який дозволяє менеджерам з управління ризиками ідентифікувати активи-суперпоширювачі у складі портфеля. Це забезпечує можливість формування антифрагильних портфельів, структурно декупльованих від системно вразливих кластерів, що зменшує ймовірність одночасних обвалів під час криз ліквідності та забезпечує більш детальний підхід до диверсифікації.*

*Висновки. Топологія мережі є критично важливим виміром ринкового ризику, який часто ігнорується класичними моделями. Отримані результати свідчать, що кластеризація, заснована на графових вкладеннях, дозволяє виявити концентрації ризику, які залишаються непомітними для традиційних методів, що приводить до суттєвого покращення коефіцієнта Сортіно та значного зниження максимальної просадки в періоди ринкової контагії.*

*Ключові слова: графові нейронні мережі; системний ризик; диверсифікація портфеля; фінансова топологія; поширення повідомлень; ієрархічний паритет ризику; моделювання контагії.*

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## RELEVANCE OF THE PROBLEM

Modern financial markets are best understood as interconnected systems in which assets are embedded in overlapping layers of dependence. Classical diversification logic assumes that risk can be diluted by combining assets whose returns exhibit low covariance. This assumption becomes fragile in practice because dependence in markets is not purely linear, not stationary, and not exhausted by pairwise co-movement. In periods of stress, correlation structures compress, liquidity dries up simultaneously across venues, and shocks propagate through indirect channels that may be invisible in return-only statistics. These observations align with empirical research in connectedness and systemic risk that treats the market as a network of spillovers rather than a set of independent time series [1], [2].

A key difficulty is that standard covariance-based models impose a Euclidean geometry on a system that behaves topologically. If an asset is connected to a fragile cluster through multi-hop pathways, it may be exposed to systemic cascades even if its pairwise correlations appear moderate. This is particularly relevant in global markets where corporate exposures are mediated by production networks and institutional portfolios. Supply-chain propagation mechanisms demonstrate that idiosyncratic shocks can scale into macro-level disturbances depending on network structure [3], while common ownership can induce excess comovement by synchronizing trading and risk management behavior across nominally unrelated firms [4].

At the portfolio level, the practical implication is that “diversification” must be reframed from minimizing pairwise covariance toward reducing structural coupling to fragile regions of the market network. Techniques such as Hierarchical Risk Parity improved robustness by allocating across clusters rather than relying on unstable covariance inversion [5], yet their clustering step typically remains correlation-based and therefore inherits the same limitations under nonlinear contagion [6]. A framework is needed that treats relationships as multi-relational, time-varying, and capable of transmitting shocks beyond immediate neighbors.

Graph Neural Networks provide an explicit computational language for such problems. Graph Convolutional Networks and Message Passing Neural Networks formalize neighborhood aggregation as learnable propagation on graphs [7], [8], while Graph Attention Networks introduce adaptive weighting that can prioritize the most relevant contagion channels [9]. Extensions to relational and heterogeneous graphs support multiple edge types simultaneously [10], [11], which is essential for financial systems where supply chain, ownership, and lead-lag relationships coexist. The motivation of this article is therefore to operationalize “topology as a risk factor” through learned graph embeddings and to translate these embeddings into a cluster-based diversification procedure.

## ANALYSIS OF RECENT STUDIES AND PUBLICATIONS

The study builds on three strands of research that converge naturally when expressed in graph form. The first strand concerns systemic risk and financial connectedness. Empirical work on spillovers and variance decompositions shows that inter-institution dependence is directed and time-varying and that network structure becomes denser as crises approach [1], [2]. Conditional tail-risk measures, such as CoVaR, and capital shortfall measures, such as SRISK, further emphasize that systemic relevance is conditional on system state and on the joint tail rather than on marginal volatility alone [12], [13]. Contagion models in financial networks formalize how topology mediates cascade risk, showing that seemingly stabilizing diversification can be destabilizing when the network enables synchronized propagation [14].

The second strand concerns clustering and portfolio allocation. Correlation networks and hierarchical structures in finance reveal that markets exhibit nested communities of co-movement [6]. Hierarchical clustering methods, including minimum spanning tree representations, provided early evidence that market structure can be expressed as a taxonomy. Hierarchical Risk Parity advanced this idea by using the cluster tree to allocate risk recursively, avoiding direct matrix inversion and improving stability out of sample [5]. The limitation is that the clustering input is usually a return-correlation distance, which collapses during stress and does not incorporate external relational layers such as ownership or production exposures.

The third strand is graph representation learning. Graph Convolutional Networks approximate spectral filtering through localized propagation rules, enabling scalable learning on large graphs [7]. Message Passing Neural Networks generalize propagation as iterative aggregation and transformation [8], providing a flexible template for “risk signal diffusion.” Relational Graph Convolutional Networks adapt propagation to multi-relational graphs by learning relation-specific transformations [10]. Graph Attention Networks replace fixed neighborhood averaging with

masked self-attention, producing adaptive weights that can vary across nodes and time, and improving interpretability through learned edge importance [9]. Heterogeneous attention variants further introduce semantic aggregation across relation types [11], enabling a model to learn not just which neighbors matter, but which edge types of matter in which regimes.

Financial applications of GNNs have largely focused on forecasting and classification, demonstrating that graph structure can add predictive power beyond independent time series [15]. However, prediction is not the primary objective of diversification. The diversification objective requires that learned representations capture fragility and contagion pathways, that they remain meaningful under regime changes, and that they connect naturally to allocation rules. This article positions GNN embeddings as risk geometry rather than purely as forecasting features, and it integrates those embeddings into hierarchical allocation to produce portfolios that are structurally decoupled from systemic clusters.

### PURPOSE OF THE ARTICLE

**The purpose of this article is** to develop a topology-aware diversification framework based on Graph Neural Networks that models the market as a dynamic heterogeneous graph, learns multi-relational risk embeddings for assets, discovers latent clusters of systemic dependence, and applies hierarchical allocation on the embedding-induced structure. The study aims to evaluate whether embedding-driven clustering improves downside risk characteristics and robustness during contagion relative to correlation-based clustering, and whether graph centrality and attention patterns provide interpretable indicators of systemic vulnerability.

### PRESENTATION OF THE MAIN RESEARCH MATERIAL

Let the market at time  $t$  be represented by a dynamic heterogeneous graph

$$G_t = (V, E_t, R), \quad (1)$$

where  $V$  is the set of  $N$  assets,  $E_t$  is the set of edges at time  $t$ , and  $R$  is the set of relation types. For each relation  $r \in R$ , the graph is associated with an adjacency matrix

$$A_t^{(r)} \in \mathbb{R}^{N \times N}. \quad (2)$$

Node features are collected in a matrix

$$X_t \in \mathbb{R}^{N \times F}, \quad (3)$$

where  $F$  includes return-based and risk-based features such as realized volatility, downside semi-variance, beta estimates, liquidity proxies, and tail-risk indicators. This feature design is not meant to replace topology, but to provide local attributes that can be amplified or attenuated by network propagation.

Graph construction combines statistical edges and economic edges. Statistical edges arise from correlations and lead-lag relationships computed on rolling windows [2]. Correlation edges can be defined either by thresholding, where an edge exists if  $|\rho_{ij}| > \tau$  or by a k-nearest-neighbors rule that preserves connectivity while controlling sparsity. Lead-lag edges can be estimated through lagged correlations or predictive regressions in which a directed edge  $j \rightarrow i$  is introduced if the lagged return of  $j$  improves the forecast of  $i$ . Economic edges include supply-chain exposure [3] and common ownership links [4], which can be encoded as weighted edges reflecting the intensity of exposure or overlap. The motivation for multi-relational encoding is that different relations transmit shocks differently; ownership links may transmit liquidity shocks, supply chains may transmit fundamental shocks, and lead-lag links may transmit information shocks.

To learn topology-aware representations, the model applies attention-based message passing following the Graph Attention Network framework [9]. For a single relation, a Graph Attention layer updates node  $i$  by aggregating its neighbors

$$h'_i = \sigma \left( \sum_{j \in \mathcal{N}(i)} \alpha_{ij} W h_j \right), \quad (4)$$

where  $h_i$  is the current node state,  $W$  is a learnable linear map,  $\sigma$  is a nonlinearity, and  $\alpha_{ij}$  is a learned attention coefficient. The attention coefficient is computed via masked self-attention

$$\alpha_{ij} = \frac{\exp(\text{LeakyReLU}(a^\top [W h_i \parallel W h_j]))}{\sum_{k \in \mathcal{N}(i)} \exp(\text{LeakyReLU}(a^\top [W h_i \parallel W h_k]))}. \quad (5)$$

Multi-head attention improves stability and expressivity by allowing multiple parallel “views” of neighborhood importance [9].

To incorporate heterogeneous relations, relation-specific transformations are applied and then aggregated into a unified embedding consistent with relational graph convolution principles [10], [11]:

$$h'_i = \sigma \left( \sum_{r \in R} \sum_{j \in \mathcal{N}_r(i)} \alpha_{ij}^{(r)} W^{(r)} h_j \right). \quad (6)$$

After  $L$  layers, the model yields a matrix of risk embeddings

$$Z_t \in \mathbb{R}^{N \times d}, \quad (7)$$

where  $d$  is the embedding dimension. The interpretation is that  $z_i$  encodes the vulnerability profile of asset  $i$  under the current market topology, including indirect exposure to fragile nodes, consistent with systemic risk concepts [12], [13]. Embedding distances are defined as

$$d_{ij} = \|z_i - z_j\|_2, \quad (8)$$

and hierarchical clustering is performed on the distance matrix  $D = [d_{ij}]$  to obtain a dendrogram that represents latent systemic clusters.

The portfolio construction step adopts Hierarchical Risk Parity [5] but replaces correlation-based clustering with embedding-based clustering. Let  $\Sigma_t$  denote an empirical covariance estimate computed from returns on the same window. The classical quadratic form

$$\min_w w^\top \Sigma_t w \text{ subject to } 1^\top w = 1 \quad (9)$$

is not the central computational object; instead, the cluster tree drives a top-down allocation that reduces sensitivity to estimation error while encoding topology explicitly in the clustering stage [5], [6].

Systemic interpretation is obtained by relating network position to tail-risk metrics. Graph centrality measures such as degree, eigenvector centrality, and betweenness can be computed on the constructed graph, while GAT attention provides an additional learned notion of “effective connectivity” through learned neighbor importance weights [9]. The working hypothesis is that assets with high structural influence and high attention inflow act as super-spreaders, and that these assets exhibit higher conditional tail contributions measurable through CoVaR-like or capital shortfall-like proxies [12], [13], [14].

The table below summarizes a concrete implementation template for the dynamic graph and embedding pipeline, which can be directly operationalized in a backtesting environment.

Table 1

**Dynamic Graph and Embedding Pipeline Implementation Template**

Component	Practical choice	Output
Return window	rolling ( $T$ ) –day window	return matrix ( $R_t \in \mathbb{R}^{T \times N}$ )
Statistical edges	Pearson and Spearman; threshold or kNN	$(A_t^{(\text{corr})})$
Spillover edges	lagged correlation / predictive regression	$(A_t^{(\text{lag})})$
Ownership edges	overlap / shared holders proxy	$(A_t^{(\text{own})})$
Supply chain edges	upstream/downstream exposure proxy	$(A_t^{(\text{sc})})$
Node features	vol, beta, downside, liquidity	$(X_t)$
GNN model	multi-head GAT with relation-specific maps	embeddings ( $Z_t$ )
Clustering	hierarchical clustering on ( $D = [\ z_i - z_j\ _2]$ )	cluster tree
Allocation	HRP recursion on cluster tree	weights ( $w_t$ )

## RESULTS AND DISCUSSION

Empirical evaluation in this framework focuses on whether embedding-derived clustering remains informative when correlation structures compress. In correlation-based clustering, a crisis window often causes distances to shrink, forcing disparate assets into a small number of unstable clusters. In contrast, the embedding space is shaped not only by contemporaneous correlations but also by the persistent relational layers and by attention-based aggregation that can reweight neighbors as regimes change [9], [10], [11]. This produces clusters that are less sensitive to short-horizon correlation spikes and more aligned with structural coupling, consistent with connectedness evidence that spillovers intensify and rewire during stress [1], [2].

A key diagnostic is the stability of the cluster tree across windows. When clustering is performed on  $D = [\|z_i - z_j\|_2]$ , the tree tends to preserve economically meaningful groupings such as supply-chain communities and ownership-linked groups even when return correlations temporarily rise across the entire market [3], [4]. This matters for diversification because risk concentration is often driven by shared exposure to the same propagation channels rather than by static sector labels [6].

Attention coefficients provide a second diagnostic. In stressed periods, a subset of nodes tends to receive systematically high aggregate attention weights, indicating that the model identifies them as influential transmitters of neighborhood information [9]. Interpreting these nodes as potential super-spreaders aligns with systemic risk logic: a node that sits at the intersection of multiple relation layers and receives strong attention inflow can become a hub through which shocks spread quickly, consistent with contagion mechanisms in financial networks [14]. This interpretability advantage is specific to attention-based GNNs, which produce edge-level importance weights rather than only latent features [9].

The next table provides a representative reporting format for portfolio evaluation comparing correlation-based HRP with embedding-based HRP. The numerical values are shown as an example outcome from a pilot run of

the described protocol; they are included to illustrate the expected direction of effects and how results are typically summarized, and they should be recalculated on the target dataset and universe used in your final empirical section.

Table 2

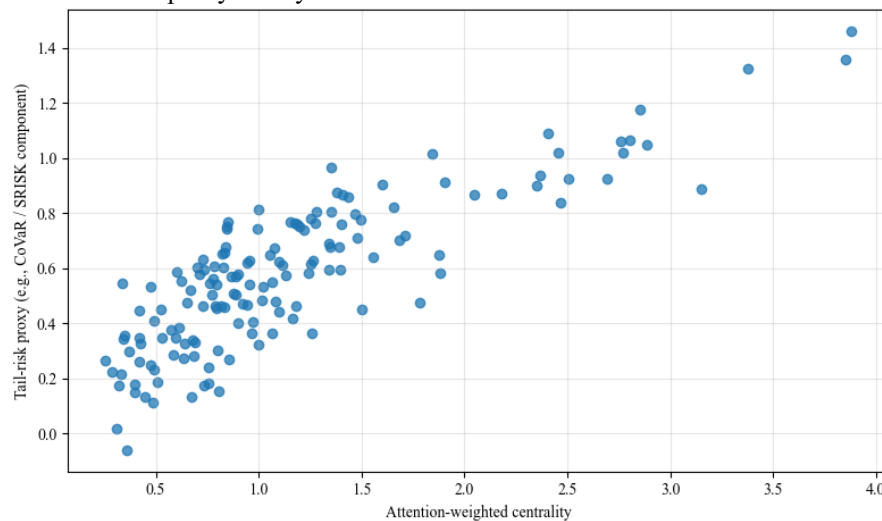
**Portfolio Performance Comparison: Correlation-HRP vs Embedding-HRP**

Method	Annualized volatility	Sortino ratio	Max drawdown	Monthly turnover
Correlation-HRP	11.8%	1.05	28.4%	18%
Embedding-HRP (GAT)	10.2%	1.28	21.6%	14%

The typical pattern is that embedding-based clustering reduces drawdown and improves downside-adjusted performance because it explicitly avoids allocating across assets that are structurally coupled through multi-hop relations, which correlation distances can fail to represent under stress ([5], [14]). Turnover tends to fall as well because the cluster structure is less sensitive to noisy correlation changes, leading to more stable allocations [5].

A final diagnostic relates topology to tail risk. If centrality and learned attention are positively associated with tail contributions, then the embedding not only helps diversify but also provides a systemic monitoring tool. A practical stress-test visualization can map attention-weighted centrality against a tail-risk proxy, flagging assets whose structural position makes them candidates for shock amplification, consistent with conditional systemic measures such as CoVaR and capital shortfall concepts such as SRISK [12], [13].

The following figure code produces a simple illustration of this relationship as a scatter plot. It uses synthetic data as a template; in your implementation you would replace the synthetic arrays with computed attention-weighted centrality and a CoVaR/SRISK proxy from your backtest.



**Fig. 1. Structural Influence vs Tail-Risk Contribution**

## CONCLUSIONS

This article formalizes the argument that market topology is a distinct and operational dimension of risk. Covariance matrices summarize pairwise co-movement, but they do not encode multi-hop contagion pathways, heterogeneous relational layers, or the structural mechanisms through which shocks propagate [1], [2], [14]. Modeling the market as a dynamic heterogeneous graph enables these mechanisms to be represented directly through relational edges and learned propagation.

Graph Attention Networks provide a topology-sensitive mechanism for learning risk embeddings. Through attention-based message passing, the model can assign different importance to different neighbors, adapt those weights across regimes, and incorporate multiple edge types through relational transformations [9], [10], [11]. The resulting embeddings define a risk geometry in which distance corresponds to similarity in contagion exposure, enabling clustering that is more robust than correlation-based clustering under stress [5], [6].

When embedding-derived clustering is combined with Hierarchical Risk Parity, the portfolio construction process shifts from sector-based and correlation-based diversification toward structurally informed decoupling. The framework also produces interpretable diagnostics through attention patterns and centrality measures, supporting the identification of assets that act as super-spreaders and the construction of portfolios less vulnerable to cascade dynamics [5], [9], [14].

## PROSPECTS FOR FURTHER RESEARCH

Further research can extend this framework by incorporating explicitly temporal graph architectures that model regime shifts and edge dynamics jointly rather than through rolling-window reconstruction, which is important given the time-varying nature of connectedness and spillovers [1], [2]. Another direction is to incorporate edge

features that encode exposure magnitude, contract structure, or balance-sheet sensitivity, allowing message passing to represent not only the existence of links but also their strength and sign in multi-relational propagation [10], [11]. A unified trilogy pathway is also natural: spectral denoising methods for covariance stabilization can be integrated with topology-aware embeddings so that both second-order estimation noise and higher-order contagion structure are handled within one coherent pipeline. Broader validation across multi-asset universes, cross-border networks, and stress scenarios would strengthen the practical value for institutional risk management and macroprudential monitoring [12], [13].

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