EFFECTS OF NETWORK CENTRALITY ON STOCK RETURNS: A LITERATURE REVIEW

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Abstract: ***This literature review examines the evolving paradigm of asset pricing by synthesizing recent research on the impact of network centrality on stock returns. Moving beyond traditional models, this review explores how the topology of production, informational, and financial networks endogenously determines risk premiums. Methodologically, the reviewed literature covers nonlinear general equilibrium models, variance decomposition frameworks, and network centrality measures applied to several markets including the United States, China, Australia, and Turkey. The findings reveal a complex, context-dependent relationship between network position and performance. In economies like the U.S., centrality in production networks functions as a chanel for spilling shocks, resulting in a significant return premium for central industries. Conversely, evidence from other markets suggests a "diversification hypothesis" where centrality offers a buffer against localized risks, leading to lower expected returns. Within informational networks, centrality facilitates superior news diffusion and alpha generation. Alhough these human-led advantages are increasingly substituted by FinTech and quantitative automation. Finally, financial sector connectedness is identified as a distinct pricing factor which captures both systemic vulnerability and credit intermediation dependence in non-financial firms.***

• Keywords: *network centrality, systematic risk, production networks, information diffusion, asset pricing.*

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1. Introduction

The investigation into the cross-sectional variation of stock returns has undergone a paradigmatic shift, moving from the analysis of isolated firm characteristics toward a complex, systemic understanding of inter-entity relationships. In the traditional landscape of finance, asset pricing models were predominantly constructed upon the premise that firm-specific idiosyncratic risks are diversified away in the aggregate, leaving only exposure to exogenous macroeconomic factors as the primary determinant of the equity risk premium. However, the maturation of financial markets and the traumatic realizations following the 2008 global financial crisis have catalyzed a burgeoning interest in the role of interconnections between firms, industries, and sectors as fundamental mechanisms for shock propagation and information dissemination. Central to this evolving field is the concept of network centrality, which serves as a metric for the relative prominence and influence of an entity based on its position within the broader economic graph.

The significance of network centrality in asset pricing lies in its potential to provide a rigorous microfoundation for systematic risk. As established in the seminal address by Cochrane, there remains a critical need to understand why some stocks exhibit higher market betas than others. Network-based research suggests that these betas are not exogenous parameters but are endogenously derived from the topology of trade flows, information conduits, and volatility spillovers. When an industry or firm occupies a central position, it acts as a “hub” or a “star” node, effectively becoming the intersection point for a multitude of conduits through which microeconomic shocks transmit and aggregate into macroeconomic fluctuations. This report serves to provide a comprehensive literature review of the effects of network centrality on stock returns, utilizing a diverse array of perspectives ranging from production-based general equilibrium models to market microstructure analyses of information networks.

The scope of this review encompasses several distinct dimensions of connectivity. First, it examines production networks, where industries are linked through customer-supplier relationships, exploring how the cascading of supply and demand shocks affects risk premiums in the United States and

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Australia (Ahern, 2013; Herskovic, 2018; Yu et al., 2024). Second, it investigates informational networks, analyzing how the connectivity of brokerage houses in Turkey or the centrality of mutual fund holdings in China influences alpha generation and information diffusion (Ni et al., 2026; Tiniç et al., 2022). Third, it explores financial connectedness, specifically the role of volatility spillovers and credit intermediation dependence in determining non-financial equity returns (Billio et al., 2023; Demirer et al., 2018).

Key concepts defined within this review include eigenvector centrality, which measures importance based on the centrality of neighbors; network density, which captures the probability of direct connections; and sparsity, which characterizes the specialization and distribution of sectoral linkages. The review is organized to first detail the methodologies employed in the field, followed by a rigorous theoretical background. It then provides a thematic analysis of empirical findings, comparing and contrasting results across different market regimes, and concludes with an identification of existing gaps and future research trajectories.

2. Methodology

The methodology for this literature review was designed to capture high-impact, peer-reviewed research and expert-level working papers that explicitly link network topology to asset pricing outcomes. The primary focus was on the synthesis of empirical evidence and theoretical modeling provided in the provided research material.

2.1. Search strategy and keyword implementation

The search strategy targeted major repositories of financial and economic research, including ScienceDirect, the Social Science Research Network (SSRN), and the Journal of Finance archives. A specific set of keywords was utilized to ensure the capture of multi-disciplinary perspectives: “network centrality,” “asset pricing,” “intersectoral trade,” “volatility connectedness,” and “information diffusion.” These terms were chosen to address both the structural aspects of the economy (production networks) and the transactional aspects (brokerage and holdings networks).

2.2. Inclusion and exclusion criteria

To maintain a specialized and nuanced perspective, the following inclusion criteria were strictly applied:

• Study Object: The research must focus on the impact of network architecture (node-level or system-wide) on expected returns, risk-adjusted alpha, or risk premiums.

• Methodology: The studies must utilize formal network measures such as eigenvector centrality, variance decomposition (Diebold-Yilmaz framework), or nonlinear dynamic stochastic general equilibrium (DSGE) models.

• Geography/Timeframe: The scope includes global equity markets, with a focus on longitudinal data spanning from the 1960s to the 2020s.

Exclusion criteria were applied to papers focusing solely on corporate governance (e.g., board interlocks) without a pricing component, or those focusing exclusively on systemic risk in banking without linkage to the broader cross-section of stock returns.

2.3. Screening and quality assessment

The selection process involved a two-stage screening. Initially, abstracts were reviewed for their relevance to the “centrality-return” paradigm. Subsequently, a full-text analysis was conducted to assess the robustness of the econometric techniques employed, such as the use of Fama-MacBeth regressions, Simulated Method of Moments (SMM), and LASSO estimation for high-dimensional networks. Quality assessment frameworks focused on the validity of the network construction ensuring that proxies for connectivity (e.g., Input-Output tables or shared holdings) were grounded in documented economic transactions or information flows.

3. Theoretical framework and background

The theoretical development of network centrality in asset pricing represents an integration of traditional macroeconomics with modern graph theory and behavioral finance. Understanding the impact of network position requires an examination of the historical debate regarding the nature of systematic risk and the mechanisms through which local shocks become global phenomena.

3.1. The shift from exogenous to endogenous systematic risk

Traditionally, macroeconomic models based on the work of Lucas (1977) suggested that sector-specific shocks should cancel out in the aggregate due to the law of large numbers. This “diversification argument” implied that unless a shock was truly economy-wide, it would have negligible effects on aggregate quantities and, by extension, on asset prices. However, more recent theories, pioneered by scholars such as Acemoglu et al. (2012), have overturned this perspective by demonstrating that if the intersectoral trade network is sufficiently asymmetric, the law of large numbers fails.

In a “star” network, where a few central industries (e.g., retail, finance, or mining) provide inputs to or purchase from many peripheral industries, a shock to the hub does not dissipate; it propagates through supply-chain linkages, creating a cascading effect. Ahern (2013) leverages this to argue that an industry’s market beta is actually an endogenous measure of its exposure to these cascading sectoral shocks. Centrality in this framework measures the likelihood that a sector will receive a random shock that is transmitting across the network. If sectoral shocks drive aggregate volatility, then industries that are more exposed to these shocks central industries must have greater exposure to economy-wide market risk and should, therefore, earn higher returns as compensation (Ahern, 2013).

3.2. Production-based asset pricing and network characteristics

The theoretical literature further distinguishes between the properties of individual nodes and the properties of the network itself. Herskovic (2018) provides a general equilibrium multisector model where sectors are connected through an input-output network. This model identifies two sufficient statistics for aggregate risk: network concentration and network sparsity.

• Network Concentration: This captures the degree to which equilibrium output is dominated by a few large sectors. When concentration is high, production is subject to diminishing returns in these large sectors, leading to lower aggregate consumption and higher marginal utility. Consequently, innovations in concentration carry a negative price of risk.

• Network Sparsity: This measures the distribution and specialization of sectoral linkages. Higher sparsity implies that firms are specializing in fewer, more efficient input sources, which leads to productivity gains and higher aggregate consumption. Innovations in sparsity thus carry a positive price of risk (Herskovic, 2018).

This is complemented by the work of Ruge-Murcia (2024), who utilizes a nonlinear dynamic equilibrium model to show how production networks endogenously generate the conditional heteroskedasticity and fat tails frequently observed in stock returns. By relaxing the assumption of identical firms and introducing heterogeneous sectors that interact via materials and investment good markets, the model demonstrates that the equity risk premium is primarily driven by sectoral shocks to investment good producers and mining, with only a limited contribution from aggregate shocks (Ruge-Murcia, 2024).

3.3. Information diffusion and market efficiency

A competing theoretical school focuses on informational centrality. Information Diffusion Theory posits that news diffuses gradually through networks of traders or funds. In an efficient market, information is reflected in prices instantaneously (Fama, 1970). However, in information networks, central nodes receive signals earlier than peripheral nodes. This creates an “informational rent” for central entities (Ni et al., 2026).

Within this school, two primary hypotheses emerge regarding the effect of centrality on returns. The Information Advantage Hypothesis suggests that centrality enhances information transmission efficiency, allowing central managers to receive high-quality signals and earn superior risk-adjusted returns (alpha). Conversely, the Limited Attention Hypothesis argues that central firms are situated at the intersection of so many conduits that their information environment is extremely complex. Bound by cognitive limits, investors may allocate less attention to these complex entities, leading to slower information diffusion and cross-predictability (Yu et al., 2024).

3.4. Major scholars and methodological paradigms

The literature is currently characterized by three primary methodological paradigms:

1) The Structural School (Ahern, 2013; Herskovic, 2018; Ruge-Murcia, 2024): Employs DSGE models and Input-Output data to link the real economy's structure to pricing factors.

2) The Connectedness School (Demirer et al., 2018; Diebold & Yılmaz, 2014): Uses variance decomposition of volatilities and returns to measure systemic spillovers.

3) The Microstructure/Network School (Ni et al., 2026; Tiniç et al., 2022): Utilizes account-level or holding-level data to construct information networks among brokers and mutual funds.

4. Summary of Reviewed Literature

The following table summarizes the key characteristics of the research papers included in this review, providing a structured overview of the current state of the field.

Authors	Research setting	Object of the study	Methodology	Main findings	Possible limitations / Further research
Ruge-Murcia (2024)	U.S. Economy (10 broad sectors)	Asset prices in production networks	Nonlinear dynamic general equilibrium model; SMM estimation; CES aggregators.	Risk premium is driven by sectoral shocks (especially investment goods and mining). Model endogenously generates fat tails and heteroskedasticity.	Small network size (10 sectors) due to computational constraints. Future research on sector-specific trends.
Tiniç et al. (2022)	Borsa Istanbul (2005–2015)	Broker network connectivity and expected returns	Network density, reciprocity, clustering coefficients; Intraday panel regressions.	Negative relationship between connectivity and one-month ahead returns. Sparse broker networks earn 1.2%–1.8% monthly premiums.	Connectivity measures are highly correlated with trading volume. Potential for multi-collinearity issues.
Ni et al. (2026)	Chinese Equity Funds (2007–2024)	Mutual fund alpha and holdings networks	Five centrality measures (Degree, Closeness, etc.); Rolling window regressions.	Central funds generate significantly higher risk-adjusted returns. FinTech adoption substitutes for human network judgment, diminishing benefits.	Chinese market is retail-dominated; network is based only on top-10 holdings. Future study on balancing technology vs. human processes.
Demirer et al. (2018)	U.S. Non-financial firms (1965–2016)	Financial sector volatility connectedness	Diebold-Yilmaz Connectedness Index (DYCI); LASSO estimation in VAR.	Negative exposure to financial connectedness predicts higher returns (15% p.a. alpha). Effect driven by intermediation dependence.	No linear relationship; risk is asymmetric and driven by firms covarying negatively with the index.
Ahern (2013)	U.S. Intersectoral trade (1983–2007)	Industry centrality in trade networks	Eigenvector centrality in Social Accounting Matrix (SAM); Two-stage regressions.	Central industries earn significantly higher stock returns (27 bps/month spread) due to greater exposure to systemic shocks.	Ambiguity in interpretation (centrality vs. omitted risk factor). Potential measurement errors in ex-post betas.
Lan et al. (2025)	China Blockchain Industry (2017–2023)	Network centrality and portfolio returns	Multilayer synthetic network; Particle Swarm Optimization (PSO); Hybrid centrality.	Investing in central firms improves returns and lowers risk (Resource-Based View). Excessive diversification weakens efficiency.	Single-industry focus; limited to listed companies. Need for capturing time-varying multi-dimensional dependencies.
Yu et al. (2024)	Australian Equity Market (1999–2019)	Domestic and Global trade networks	IO tables; Cross-predictability and Momentum tests; Fama-MacBeth.	Central industries yield *lower* returns due to diversification. Information transmission is *slower* among central firms due to complexity.	Australian market is skewed/concentrated in top 300 stocks. Global centrality shows limited predictive power for domestic returns.
Herskovic (2018)	U.S. Stocks (1979–2013)	Production network asset pricing factors	Multisector model with network concentration and sparsity; Portfolio sorting.	Sparsity beta earn 4.6% spread (positive risk price); Concentration beta earn -3.2% spread (negative risk price).	Cobb-Douglas assumption limits substitution patterns. Reliance on 5-year BEA IO updates.
Billio et al. (2023)	Fama-French 48 sector portfolios	Network connectivity and factor exposure	Network-augmented linear factor model; Structural simultaneous equations.	Network links inflate common factor exposures. Traditional models are misspecified if ignoring links (correlated/heteroskedastic residuals).	No single prevailing network estimation approach. Assumptions on time-invariance vs. time-variation in R.
Procházková (2020)	SP 500 Index (2005–2018)	Volatility/return connectedness as risk factors	Fama-MacBeth two-step regression; Variance decomposition (DY framework).	Overall sector connectedness is a significant risk factor. Directional "FROM" connectedness increases risk premium.	Volatility connectedness is more informative than return connectedness. Methodology limits for very large datasets.

Source: Synthesized by the authors

5. Review of themes and findings

The analysis of the effects of network centrality on stock returns reveals a complex interplay between market structure, economic fundamentals, and informational frictions. The literature can be categorized into several prominent themes that highlight the diversity of network effects across different geographies and asset classes.

5.1. Theme 1: Methodologies for measuring centrality and risk

A defining characteristic of this domain is the methodological rigor required to move from raw transaction data to a meaningful network representation. The reviewed literature utilizes three primary approaches for network construction and parameter estimation.

5.1.1. Graph-theoretic approaches and centrality measures

The most common approach involves using Input-Output tables or Social Accounting Matrices to define the edges of a trade network. Ahern (2013) and Yu et al. (2024) utilize eigenvector centrality, which assumes that the importance of a node is proportional to the sum of the centralities of its neighbors. This measure is particularly suited for capturing the feedback effects inherent in production chains for instance, an oil shock affecting transportation, which subsequently affects the oil industry (Ahern, 2013). Tiniç et al. (2022) expand this by using local connectivity measures such as weighted clustering coefficients to capture triangle-pattern trade flows in order-driven markets.

5.1.2. Variance decomposition and connectedness

A second paradigm, epitomized by the Diebold-Yilmaz framework (Diebold & Yılmaz, 2014), uses generalized forecast error variance decompositions from vector autoregressions (VAR) to measure connectedness. This approach is highly effective for identifying volatility spillovers and "fear" transmission within the financial sector (Demirer et al., 2018; Procházková, 2020). Because it does not require balance-sheet data, it allows for high-frequency analysis of how shocks to one entity's future uncertainty are caused by shocks in another entity. Demirer et al. (2018) employ LASSO estimation to extend this framework to high-dimensional environments, ensuring sparsity in the approximating model while preserving the non-linear transformation of connections in the variance decomposition.

5.1.3. Structural DSGE and multi-layer synthesis

The structural school utilizes general equilibrium models to derive asset pricing factors directly from production technology parameters. Herskovic (2018) derives concentration and sparsity as sufficient statistics for risk, while Ruge-Murcia (2024) uses Simulated Method of Moments (SMM) to estimate separate elasticities of substitution for material inputs and investment goods. In contrast, Lan et al. (2025) represent the vanguard of emerging methodologies, utilizing multilayer networks that integrate Pearson, Kendall tau, and Spearman correlations, with weights optimized via Particle Swarm Optimization (PSO). This approach allows for the extraction of multifaceted market dependencies that a single correlation metric would oversimplify.

5.2. Theme 2: Production networks and the determinants of systematic risk

The core debate in the literature surrounds whether network centrality serves as a source of risk or a source of safety.

5.2.1. The centrality premium and cascading shocks

Ahern (2013) provides robust empirical evidence that in the United States, central industries earn significantly higher returns (approximately 3.2 percentage points per year spread between the highest and lowest quintiles). This finding supports the hypothesis that centrality increases exposure to systematic risk. Central sectors are more likely to receive shocks transmitting across the network; they covary more closely with market returns and future consumption growth. This effect is present even in unlevered returns, suggesting it is a compensation for operating risk rather than financial risk (Ahern, 2013). Ruge-Murcia (2024) corroborates this by demonstrating that sectoral shocks to investment good producers and mining drive the majority of the sectoral equity risk premia, while the contribution of aggregate shocks is limited.

5.2.2. The sparsity-concentration duality

Herskovic (2018) refines the production-based perspective by identifying how network changes are priced. Innovations in network sparsity (input specialization) carry a positive price of risk, as they increase efficiency and aggregate consumption, leading to a 4.6% annual return spread. Conversely, network concentration (dominance by few large sectors) leads to lower aggregate returns due to diminishing returns on investment, carrying a negative price of risk and a -3.2% return spread. This suggests that the cross-section of returns is sensitive not just to where a firm is, but to how the overall network structure is evolving toward specialization or concentration (Herskovic, 2018).

5.2.3. The diversification hypothesis: Evidence from Australia

In a significant divergence from the U.S. results, Yu et al. (2024) find that central industries in the Australian market yield lower returns. They argue that central firms benefit from diversified trade relations, making them less reliant on any single partner and thus more resilient to localized shocks. This “diversification effect” outweighs the contagion risk in the Australian context. This suggests that the relationship between centrality and returns is contingent on market structure the Australian market is heavily skewed toward a few sectors (mining and banking), which may alter the propagation dynamics compared to the more diversified U.S. industrial base (Yu et al., 2024).

5.3. Theme 3: Information diffusion, brokers, and managerial alpha

Networks also function as informational conduits, where centrality dictates the speed and quality of news processing.

5.3.1. Broker network connectivity in Turkey

Tiniç et al. (2022) provide critical insights into broker networks in order-driven markets. They find a negative relationship between connectivity and returns, where stocks in the lowest connectivity quintile earn a monthly premium. Intraday panel regressions document that dense broker networks are associated with more efficient diffusion of information and a decrease in the adverse selection component of the spread. This suggests that connectivity reduces information asymmetry; investors demand a premium for holding stocks with sparse broker networks because those stocks are more opaque and prone to informed trading rents (Tiniç et al., 2022).

5.3.2. Mutual fund centrality and the FinTech disruption in China

Ni et al. (2026) examine the informational advantages of fund managers. They find that funds with more central network positions (based on shared holdings) generate significantly higher alpha. This requires “active human management” to transform soft information from peer interactions into concrete portfolio actions. However, the rise of FinTech and quantitative strategies acts as a “substitution effect," where automated systems replace human judgment. For funds with high FinTech adoption, the marginal benefit of network centrality disappears, thus highlighting a shifting trade-off in modern asset management (Ni et al., 2026).

5.3.3. Complexity and Investor attention constraints

Yu et al. (2024) explore the "Limited Attention Hypothesis," finding that information transmission is slower for central firms. Because central firms have a larger number of trading partners, their information environment is more complex. Cognitive resources of investors are scarce; therefore, they tend to allocate less attention to complicated central firms, focusing instead on simpler peripheral ones. This leads to increased "cross-predictability," where returns can be predicted by the past performance of supply-chain partners, an effect that is significantly more prevalent in high-centrality industries (Yu et al., 2024).

5.4. Theme 4: Financial connectedness and intermediation frictions

The propagation of risk through financial networks represents a distinct channel of network influence on returns.

5.4.1. Volatility connectedness and systemic risk

Procházková (2020) demonstrates that volatility connectedness serves as a more informative measure than return connectedness, as returns are generally less persistent. In the SP 500, sector-wide connectedness is a significant risk factor. Specifically, "FROM" connectedness the share of an asset's uncertainty explained by shocks from others is a significant predictor of the risk premium in sectors such as financial, health care, and consumer discretionary. Billio et al. (2023) theoretically ground this by showing that network interconnections "inflate" factor exposures. An asset may appear to have high exposure to a macro-factor not because of its own fundamentals, but because it is linked to a sector that is fundamentally exposed.

5.4.2. Dependence on financial intermediation

Demirer et al. (2018) identify the "Connectedness Beta Anomaly." Non-financial firms whose returns covary negatively with a financial sector volatility connectedness index earn an annual risk-adjusted return of 15%. This exposure serves as a proxy for dependence on financial intermediation. When financial sector connectedness is high (signaling systemic stress), firms that are young, small, or have low credit quality find it difficult to satisfy their financing needs. This creates a disproportionate effect on their risk premiums, which traditional factors (size, B/M, momentum) fail to subsume (Demirer et al., 2018).

5.5. Theme 5: Emerging sectors and the blockchain case

In nascent industries, network centrality plays a role in identifying strategic resource advantages. Lan et al. (2025) find that in the China blockchain industry, central firms consistently outperform peripheral ones. This is explained through the Resource-Based View (RBV): central firms have better access to the new resources, knowledge, and innovation hubs necessary to survive in a volatile digital market. Peripheral firms, conversely, lack the connections to build competitive advantages and face higher risk without commensurate returns (Lan et al., 2025).

6. Synthesis and comparative discussion

The synthesis of the reviewed literature reveals significant contradictions that provide deep insights into the conditionality of network effects.

6.1. The risk versus diversification paradox

The fundamental tension in the literature is whether centrality signifies risk exposure (Ahern, 2013) or a diversification buffer (Yu et al., 2024). The resolution of this paradox likely lies in the market's industrial concentration. In the U.S., a highly integrated and diverse economy, central industries are the primary conduits for aggregate risk. In Australia, a resource-based economy with high sectoral concentration, centrality provides a means of spreading risk across more partners. This suggests that the "price of centrality" is not a constant but a function of national economic architecture.

6.2. Direct versus indirect factor exposure

Billio et al. (2023) and Ahern (2013) both emphasize that ignoring network links leads to misinterpreting market betas. By disentangling direct exposures (structural) from indirect exposures (network-induced), researchers can more accurately identify the sources of systematic risk. The findings of Demirer et al. (2018) regarding financial sector spillovers suggest that what is often labeled as "idiosyncratic risk" in non-financial firms is, in reality, a systematic vulnerability to credit market connectedness.

6.3. The evolution of information efficiency

The evidence from Turkey and China suggests that informational centrality creates "informational rents" that are exploitable by human managers but erased by quantitative automation (Ni et al., 2026; Tiniç et al., 2022). This implies that as global markets become more "quant-driven" and "FinTech-integrated," the alpha available from being a central node in an information network may decay. However, the structural systematic risk identified in production networks remains an enduring feature of the physical economy that cannot be automated away (Herskovic, 2018).

7. Conclusion

This comprehensive review has explored the multifaceted role of network centrality in determining stock returns across global equity markets. By synthesizing research from structural equilibrium models, volatility connectedness indexes, and information network theories, several definitive conclusions emerge.

7.1. Summary of insights

Network centrality is a potent, yet conditional, determinant of stock returns. In large, integrated economies, centrality in production networks typically functions as a conduit for systemic shocks, leading to higher returns and market betas (Ahern, 2013; Herskovic, 2018; Ruge-Murcia, 2024). In more concentrated or specialized economies, centrality can offer a diversification benefit that reduces expected returns (Yu et al., 2024). Within informational networks, centrality provides fund managers with an "alpha advantage" that is increasingly threatened by the rise of FinTech and quantitative investment strategies (Ni et al., 2026; Tiniç et al., 2022). Finally, financial sector connectedness creates a distinct pricing factor related to credit intermediation dependence, particularly affecting small and vulnerable firms (Demirer et al., 2018).

7.2. Identified gaps and limitations

Despite the richness of the current literature, several critical gaps remain. Most empirical studies rely on static or infrequently updated network data (e.g., BEA IO tables updated every 5 years). There is a significant lack of research into high-frequency, time-varying network architecture and how sudden structural breaks (e.g., the collapse of a major global supplier) impact returns in real-time. Furthermore, the majority of the research focuses on domestic networks; in a globalized economy, a firm's position in an international supply chain may be more relevant than its domestic position (Yu et al., 2024). Finally, the "black box" nature of many modern multi-layer and machine-learning-based network models (Lan et al., 2025) requires more transparent theoretical grounding to ensure findings are not merely artifacts of over-optimization.

7.3. Suggestions for future research

Future inquiry should focus on the development of dynamic network asset pricing models that integrate real-time transactional data from digital trade platforms. There is a profound opportunity to investigate the interaction between network centrality and ESG (Environmental, Social, and Governance) factors specifically, how sustainability shocks propagate through trade links. Additionally, understanding the evolving trade-off between technological automation and human network judgment will be essential as asset management enters the next phase of its digital transformation. Researchers should also aim to expand cross-country comparisons to determine how national industrial policies influence the "centrality-return" relationship.

In conclusion, network centrality has established itself as an essential concept for understanding the structural and informational determinants of the equity risk premium. As financial systems become increasingly interconnected, the ability to decode the topology of these connections will be paramount for both academic asset pricing and practical portfolio management.

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