Multilayer Networks in Finance: A Systematic Review

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Multilayer Networks in Finance: A Systematic Review

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Abstract

Stress in the global financial system propagates through multiple channels, including interbank credit and funding, overlapping portfolios, and bank–firm exposures. Multilayer networks represent these channels as interdependent layers, enabling analysis of how shocks transmit and amplify within and across channels. Yet many studies collapse these channels into a single layer, and stress tests often examine channels in isolation, in both cases removing cross-channel feedback and understating systemic vulnerability. This can lead to inadequate capital and liquidity buffers, overly optimistic risk assessments, and poorly targeted interventions. The synthesis in this review shows how multilayer financial networks are constructed and quantifies how much single-layer proxies underestimate systemic vulnerability, distilling the evidence into a practical Map–Monitor–Test–Intervene workflow that serves researchers designing multilayer propagation studies, practitioners assessing portfolio and counterparty risks, and supervisors calibrating stress tests. We synthesise 112 studies (2015-2025) across six domains: Bank–firm Networks, Corporate Networks, Global Trade and Supply-Chain Networks, Interbank Networks, Financial Markets, and Global Systemic Risks. Reported magnitudes include up to 90% understatement of systemic risk when a single exposure layer is analysed in isolation, up to 50% of systemic risk missed when overlapping portfolios are omitted, and critical leverage thresholds overstated by 45% to 300% when cross-channel interactions are ignored. Three findings recur: layers encode distinct mechanisms, so one layer is often a poor proxy for another, with overlay aggregation hiding feedback; cross-layer coupling amplifies losses and tightens stability margins; and systemic importance depends on the state of the financial system, concentrating in a small minority of institutions that bridge multiple channels. Collapsing channels is no longer a harmless simplification when stability judgements, risk management, and policy decisions depend on how financial stress propagates.

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Contents

1 Introduction

1.1 Financial globalisation and multi-channel stress transmission

Global financial markets have expanded substantially since the 1970s, alongside rising instrument and transaction complexity [1, 2]. Evolving regulatory frameworks, increased multinational economic activity, technological advances, and financial innovation have shaped that expansion. As a result, financial stability, understood here as the resilience of institutions and markets to shocks, is more easily undermined by disruptions that propagate across products and jurisdictions. With deeper financial globalisation and market integration, financial stress, a system-wide disruption to funding, liquidity, and risk transfer, often transmits rapidly across markets and jurisdictions. Shocks that originate in one part of the system can then spill over into real economic activity elsewhere.

One indicator of this structural growth is the non-bank financial intermediation (NBFI) sector, which accounted for around 49% of global financial assets in 2023. NBFI assets grew by 8.5% relative to 2022, significantly outpacing the 3.3% growth observed in bank assets [3, 4]. Global exchange-traded funds (ETFs) have also grown substantially over this period, reaching around \$19 trillion of assets by November 2025, with the number of new financial products hitting a record high of 2,759 [5]. Together, these shifts have expanded market-based intermediation and widened the range of channels through which liquidity and funding stress can spread, particularly through common asset holdings and high leverage that trigger forced sales or rising margin demands.

Since the Global Financial Crisis in 2008, the growth in market-based finance, including open-ended funds and leveraged trading strategies, has been linked to higher common investor exposures and to amplification through overlapping portfolios, liquidity mismatches, and procyclical margin and collateral dynamics, where cash and collateral demands rise as volatility increases [6]. In ETFs, when secondary market liquidity is thin and dealers have limited capacity to absorb sales, stress can build around market makers and authorised participants before spilling over into wider financial markets. In open-ended funds, liquidity mismatches can intensify this dynamic by forcing asset sales to meet redemptions, reinforcing price declines and margin pressures.

Recent episodes of financial stress have revealed significant cross-market interdependencies. The margin and collateral dynamics during the March 2020 "dash for cash" [7] and the 2022 UK gilt crisis involving liability-driven investment strategies [8] show how quickly stress can propagate when leverage, collateral, and market liquidity interact. The 2021 collapse of Archegos Capital Management [9] illustrates the same dynamic. Losses propagated across prime brokers through equity swaps, margin calls, and collateral chains, spanning multiple risk channels that single-layer models tend to underestimate or miss entirely. These episodes show how derivatives, collateral arrangements, dealer balance sheets, and cash and securities markets interact in ways that can outpace regulatory response. This has shifted policy focus towards improving margining practices and liquidity preparedness for margin calls and collateral demands [6]. Technology advancements are also reshaping both the channels through which financial stress and operational disruption propagate, and the data available to map them. For example, the migration to ISO 20022, a payment messaging standard with richer counterparty and instrument fields, enables multiplex networks to be constructed directly from transaction-level payment and settlement records, representing bilateral obligations and exposures in finer detail [10]. Real-time payments also increase data granularity, but they can concentrate operational dependence on a smaller set of technology providers. That dependence, combined with rising cyber risk, creates additional routes through which operational disruption can spread across institutions and markets, routes that are usually absent from models built solely on contractual financial exposures [11–13].

These developments mean that financial stress can be amplified as it spreads simultaneously through multiple channels, including credit exposures, funding links, margin and collateral practices, portfolio overlap, and market liquidity. In stress-testing models, these channels interact, but they are not interchangeable. Nevertheless, many empirical studies collapse distinct mechanisms into a single-layer network. Doing so can understate losses, misrank systemic importance, and obscure whether amplification is dominated by credit, funding, collateral, or price dynamics. This motivates multilayer network representations, where each channel is modelled as a separate layer and between-layer interactions are kept explicit.

Many existing reviews and modelling frameworks either pre-date multilayer methods or focus on single domains. This leaves researchers, regulators, and practitioners without a consolidated view of the extent to which single-layer proxies understate systemic risk, and without a practical guide to implementing and using multilayer tools. A related gap is that stress-test designs often examine channels in isolation, which can miss non-additive amplification and lead to calibration against the wrong mechanism, for example treating solvency risk as dominant when the binding constraint is liquidity, margin capacity, or market depth.

Objectives. This review has three objectives. First, we characterise how multilayer financial networks are constructed in practice and synthesise diagnostics of layer distinctiveness, including overlap, concentration, reducibility, and horizon separation. Second, we extract reported magnitudes of the extent to which single-layer or single-channel proxies can understate losses, shift systemic importance rankings, and overstate stability margins. Third, we distil the evidence into an operational Map–Monitor–Test–Intervene workflow for risk monitoring, stress testing, and informing research design, risk management, and policy responses, developed in the *Conclusions and Outlook* section.

Coverage, contribution, and structure. This review synthesises research on multilayer networks applied to finance using 112 studies published between 1 June 2015 and 31 May 2025. We examine how studies construct layers, what methods they apply, what quantitative benchmarks they report when compared with single-layer baselines, and what those results imply for stress-testing, supervision, and financial risk management. The contribution is a consolidated, evidence-based synthesis that summarises when and how multilayer representations outperform single-layer models. It provides methodological benchmarks for researchers, operational guidance for practitioners and supervisors, and translates the evidence into a practical Map–Monitor–Test–Intervene workflow. Across the corpus, the implication is that single-layer proxies can distort inference, and layered measurement, monitoring, and intervention design can materially change conclusions for supervision and risk management.

Section 2 documents the search protocol and screening workflow using PRISMA (Preferred Reporting Items for Systematic Reviews and Meta Analyses) as a reporting guideline, alongside eligibility criteria and the evidence synthesis criteria for quantitative comparisons. Section 3 summarises the search and screening outcomes and presents the corpus overview, including the domain organisation and summary tables that condense the evidence synthesised across Sections 4 to 9. The main synthesis is then organised into six application domains, each intended as a stand-alone unit so that readers can focus on their particular area of interest, whether their interest is methodological, empirical, or policy-oriented. Section 10 concludes with limitations, practical recommendations, and a short research agenda. Three non-core but illustrative applications are synthesised in Appendix B. These do not fit cleanly into a single application domain, but they remain relevant as financial applications of multilayer networks.

Reader Guidance. It is intended that a reader reads the abstract, introduction, Section 2 and Section 3, including the summary tables. Then choose to digest the one or two sections they are most interested in, ending with the main conclusion. Because of this intended design, each section is designed to be self-contained and stand-alone, which inevitably leads to repetition of some concepts across the review paper.

1.2 Multilayer Network Concepts, Definitions, and Methods

We define and use the following terms. A *multilayer network* is a network of coupled layers, where each layer encodes a relation, mechanism, or interaction, and where links or coupling rules can connect nodes within and between layers. Layers may share the same node set or have layer-specific node sets. Figure 1 illustrates a generic multilayer network that represents these concepts. A *multiplex network* is the special case of a multilayer network where all layers share the same node set. An *overlay* is a single aggregated network formed by collapsing multiple layers using a specified aggregation rule, for example the union for binary ties or a weighted sum when link weights are on a common scale or have been normalised. This collapsing step often removes information essential for detecting systemic risk, analysing transmission pathways, and designing interventions or mitigations. A *single-layer proxy* is any reduced representation that uses one layer, or an overlay, in place of a multilayer representation when the underlying system contains multiple economically distinct channels. Figure 2 illustrates these definitions. A *financial network* represents a financial system, and adjacent economic infrastructures, as nodes and edges, where nodes can be institutions, firms, countries, or instruments, and edges represent transactions, dependencies, or flows. In this review, financial applications include banking and capital markets, payment and settlement systems, corporate finance linkages, and macro financial structures such as trade, supply chains, and policy frameworks when they directly shape financial propagation channels.

When is a multilayer framework warranted? Multilayer structures should be adopted only when separating transmission channels is likely to change decision-relevant conclusions for research, supervision, or risk management. In practice, that means identifying which channels dominate risk transmission, which institutions matter most, and what capital, liquidity, or collateral buffers are implied under financial stress. When

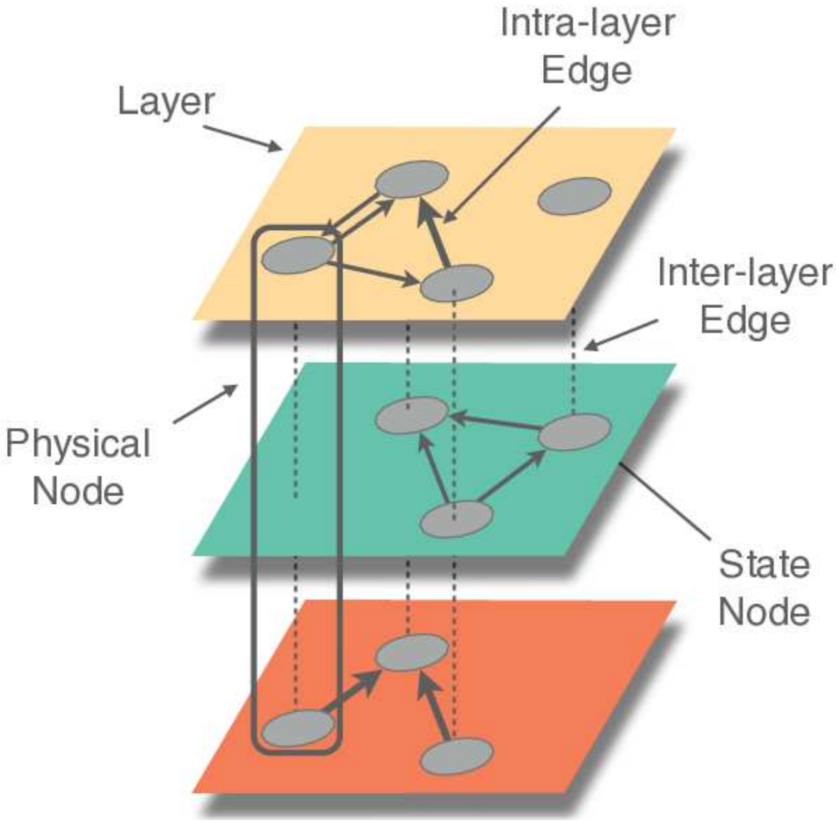

Fig. 1: Schematic of a multilayer network. Layers encode different types of relationships among nodes, occurring simultaneously. Nodes can exist in several layers, but not necessarily in all layers: 'state nodes' are nodes related to a specific layer whereas 'physical nodes' do not depend on any specific layer. Connectivity within each layer is defined by intralayer edges, whereas interlayer edges define connections across layers. Figure courtesy of M. De Domenico [14].

channels are weakly coupled or when data only support an aggregate view, a single-layer representation may be adequate, but when economically distinct mechanisms interact, aggregation can hide amplification and misattribute the dominant channels. For example, in a study modelling intranational supply chains using a multilayer network [15], intralayer links account for only 22% of monetary supply chain flows, with the remaining 78% occurring via interlayer links. This implies that total multilayer flow volume is about 4.6× larger than a single-layer-only view, illustrating a multilayer framework that preserves material transmission structure that a single-layer model discards

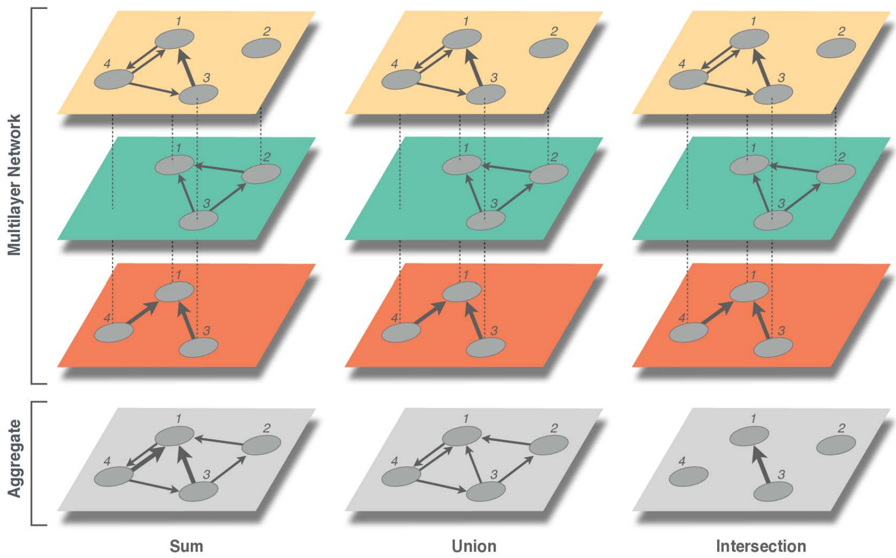

Fig. 2: Multilayer Aggregation Methods. Figure courtesy of M. De Domenico [14].

2 Systematic Search and Review Method

2.1 Review Protocol and Standards

The search and screening workflow follows PRISMA as a reporting guideline to support transparency and replicability [16]. Due to heterogeneity in metrics, samples, and designs, we employed narrative synthesis rather than quantitative meta-analysis. The search and review protocol aimed to identify, evaluate, and synthesise research on multilayer network applications in finance. Database-specific search strings are reported in Appendix A.2. Detailed eligibility criteria and the stage-specific study selection workflow are reported in Appendix A.3 and Appendix A.4. Section 3 and Figure 3 summarise the selection counts.

2.2 Search Definitions

The search and screening steps rely on consistent terminology, defined in Subsection 1.2. We used a broad family of multilayer terms, with full search strings listed in Appendix A.2.

2.3 Search Strategy and Data Sources

We searched ten academic databases to capture interdisciplinary research spanning multilayer network science and finance. Search strings combined multilayer terms and finance terms using Boolean operators, with database-specific syntax reported in Appendix A.2. The inclusion window for studies runs from 1 June 2015 to 31 May 2025. Searches were last updated on 16 June 2025 to ensure capture of papers accepted or published within that window.

2.4 Eligibility Criteria for Screening

We screened for studies that (i) use multilayer network methods (Subsection 1.2), (ii) apply them to financial systems (Subsection 2.2), (iii) were published or accepted between 1 June 2015 and 31 May 2025, and (iv) are available in English. Detailed inclusion and exclusion criteria, including reasoning, are reported in Appendix A.3.

Working paper handling and the treatment of grey literature are reported in Appendix A.3.

2.5 Study Selection Process

Study selection proceeded in four stages: within database deduplication, abstract screening with targeted full-text checks, cross-database deduplication, and reference list screening. The full stage-specific counts, together with the citation threshold rule and exclusion rationale, are reported in Appendix A.4 and summarised in Figure 3.

2.6 Use of Generative Artificial Intelligence

Artificial intelligence (AI) tools were used only for editing tasks, including grammar, spelling, punctuation, restructuring, and minor sentence smoothing, and during the paper search, Semantic Scholar (Ai2 Paper Finder) was used as a search database. AI tools were not used for screening decisions, data extraction, or interpretation, with the study design, literature search, data collection, and substantive analysis, synthesis, and interpretation carried out by the authors.

2.7 Synthesis Framework and Quality Assessment

The synthesis of the 112 paper corpus utilised a structured data extraction template informed by an adaptation of the CASP (Critical Appraisal Skills Programme) [17]. The extraction template recorded bibliographic details, application domain, network model classification, mathematical formalism, data sources, key findings, quality indicators, limitations, and future research directions; full details are provided in Appendix A.

Quantitative findings were synthesised narratively rather than through formal meta-analysis, given heterogeneity in metrics and designs. Reported magnitudes were treated as transferable when the source study reported an explicit comparison between a multilayer model and a single-layer baseline on the same sample and horizon, and the metric was defined consistently with standard usage in the literature (e.g., expected loss, DebtRank, critical leverage threshold). Table 1 consolidates representative benchmarks using these criteria, with source notes indicating the source study for each figure.

2.8 Quantitative orientation and guidance

Where studies report them, the review extracts network diagnostics such as connectedness, overlap, and modularity, and records any available computational benchmarks (for example runtime comparisons) plus classification or attribution performance. Material understatement factors are quoted where single layers replace multilayer structures, and amplification magnitudes are summarised where financial and real-economy layers interact.

Caution is advised when results hinge on design choices like filters, window selection, or horizons. Data availability, coverage, quality, and computational demands for large simulations remain key constraints. Connectedness measures statistical association, and reciprocity measures directional symmetry; neither implies causal transmission. Where studies report results only in graphs, we extract approximate values. Model and simulation parameter choices are reported where relevant, and the review distinguishes qualitative insights from quantitatively identified findings.

3 Results

3.1 Search Results

The study selection process yielded 112 publications for synthesis. Figure 3 summarises the identification, screening, and inclusion stages, including stage-specific counts, with reasons for exclusion and extended procedural detail reported in Appendix A.4.

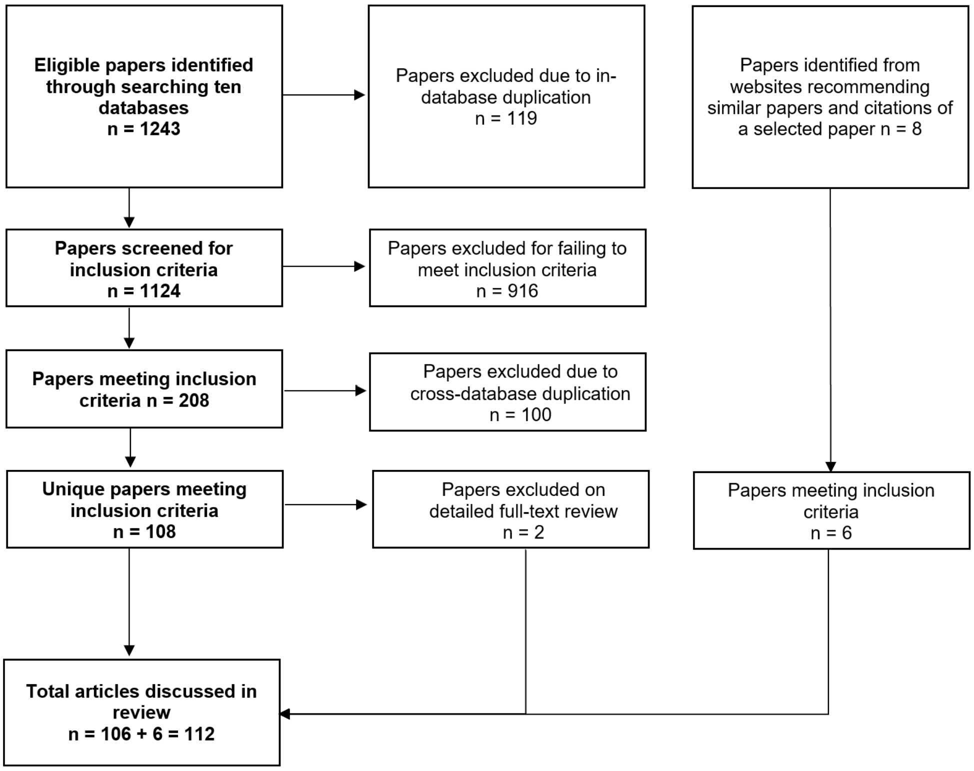

Fig. 3: PRISMA 2020 flow diagram

3.2 Synthesis Overview and Methods Employed Across the Corpus

This review organises the 112 publications into six domains of financial applications. The domains reflect distinct financial settings and layer constructions, while retaining a consistent single-layer versus multilayer comparison throughout. The six domains are: Bank–firm Networks, Corporate Networks, Global Trade and Supply-Chain Networks, Interbank Networks, Financial Markets, and Global Systemic Risks. The papers are categorised by their primary domain, whilst acknowledging that financial systems inherently span multiple categories. Hence, the groupings follow each paper's main contribution or primary application, though several papers straddle categories.

Three cross-cutting studies develop diagnostics or methodological frameworks evaluated across multiple domains or on synthetic data. These are considered non-core applications and they are synthesised in Appendix B.

Tables 1 and 2 summarise the application domains, key layers, primary findings, quantitative benchmarks, and methodologies used in the cited studies. Together they provide a compact overview of the evidence synthesised in Sections 4 to 9. Table 1 is domain-organised with quantitative benchmarks; Table 2 is method-organised with analytical purpose. Both point to the detailed synthesis in Sections 4 to 9.

For Table 1, each column is designed to separate scope, mechanism, and evidence strength, so readers can scan domains quickly while still seeing what underpins the headline comparisons. It is structured as follows:

- *Domain:* groups studies by the primary financial setting and typical layer architecture, matching the synthesis structure in Sections 4 to 9.
- *Sec.:* points to the section where that domain is synthesised in full.
- *Papers:* reports the number of studies contributing to that domain summary.
- *Key Layers:* lists the main channels represented as layers in that domain, to make the layer construction comparable across domains.
- *Primary Findings and Headline Figures:* summarises Sections 4 to 9, providing qualitative synthesis for the domain, stated at the mechanism level, and quantitative values that report the main numerical benchmarks from the synthesis. These are study specific, scenario based, and rounded.

Table 1: Summary of Multilayer Networks in Finance

Domain	Sec.	Papers	Key Layers	Primary Findings and Headline Figures
Bank–firm Networks	4	9	Interbank lending, bank–firm credit, cross-shareholdings	Bank–firm feedback loops amplify losses beyond single-layer estimates. Overlapping borrower exposures amplify distress transmission by synchronising lender losses and creating paths for spillovers into other layers [18]. Shared borrower exposures are structural, not coincidental. In Spain (2007), across 1,770 pairs of industry sectors, 96% show more shared lending exposure than expected by chance [18]. When preserving each bank's number of links (degree) and total lending (strength), 41% to 64% of sector pairs continue to show statistically significant overlap [18]. Colombia (2018 configuration): the maximum impact from a single high-exposure commercial firm default could erode $\sim$ 84% of aggregate bank equity through network propagation [19]. Required equity ratio for stability is understated by $\sim$ 9% when the interbank channel is omitted ($\sim$ 10% vs $\sim$ 11%) [20].
Corporate Networks	5	6	Ownership, boards, investor ties, firm-level supply chains, price-based (returns, volatility, tail)	Firm-level production networks coupled to bank credit exposures amplify bank losses and tail risks beyond bank-only models. Entropy tests reveal that corporate network layers are structurally irreducible and non-redundant [21]. Relative to bank-only models, when firm-level supply-chain contagion is coupled with bank exposures, banks' risk metrics materially increase: Expected Loss (EL) by 5.2×, Value at Risk (VaR) 6.7×, and Expected Shortfall (ES) 4.4× (Hungarian calibration; 20 banks; 10,000 shock scenarios) [22].
Global Trade and Supply-Chain Networks	6	7	Trade flows by sector, primary and secondary industries, financial positions	Sectoral trade multiplexes show that relatively small layers can drive cascades, and intranational input-output flows are predominantly between sectors, with the probability of large cascades (many collapsed nodes) varying sharply by layer. Community detection aligns more closely with country partitions than sector partitions, consistent with country groupings behaving as communities [23]. Primary industry trade layer $\sim$ 21% of combined trade weight, much smaller than the secondary goods layer $\sim$ 79% yet instrumental in driving multiplex cascades [24]. In supply chains, 22% of monetary flows are within-sector links and 78% are between-sector links. This implies that single-layer sector networks exclude the majority of transmission routes, as between-sector coupling carries $\sim$ 3.5× the flow of within-sector links. This coverage shortfall means total flow coverage is $\sim$ 4.6× larger when cross-sector links are included [15].

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Table 1 continued

Domain	Sec.	Papers	Key Layers	Primary Findings and Headline Figures
Interbank Networks	7	12	Unsecured and secured funding, securities holdings, derivatives, payment flows, overlapping portfolios	Overlapping portfolios transmit stress faster than credit and funding links. Interaction across layers creates non-additive amplification. A Peru application shows that neglecting the multiplex structure in favour of a single-layer representation could understate some institutions' systemic impact by up to 30% (the calculation of this is not shown explicitly in a table or figure) [25]. They also report a maximum system-wide impact of around 6.5% of total capital (DebtRank, monthly sample). In Europe, indirect losses (losses caused by spillovers through interbank and portfolio links rather than the initial shock) are 21% to 24% of total losses, with aggregate vulnerability of 14% to 16% of equity losses. Overlapping portfolios account for most defaults [26].
Financial Markets	8	32	Returns, volatility, tail-dependence and extreme risk, liquidity channels, institutional ties, implied risk layers (implied variance and variance risk premium), market infrastructure	Market layers are non-redundant, so each layer adds distinct information relative to an overlay, and layers are crisis-sensitive. Volatility and implied-risk layers dominate transmission in stress windows, and crises reweight spillovers towards longer time horizons. Single-layer proxies can omit a large share of multiplex links. Institutional and infrastructure concentration creates hidden propagation paths that aggregation suppresses. Edge sets differ sharply by layer, with up to $\sim 70\%$ of edges in a given dependence layer being unique, hence collapsing to a single layer can drop most links that exist only in specific channels [27]. In a multiplex with three modalities (returns, realised volatility, volume), overlap across all layers is very low (Jaccard similarity $\sim 7.95\%$), and modularity falls from ~ 0.90 in single layers to ~ 0.56 when layers are stacked, consistent with layer non-redundancy and information loss under overlays [28]. In dynamic networks, the return-layer uniqueness edge ratio (i.e. the share of edges that appear only on the return layer) is 9.7% versus 1.0% in static overlays [29]. Aggregating across time can remove links that exist only in specific periods. Therefore, the return-layer structure is more visible in temporal networks than in static overlays [29, 30].

Continued on next page

Table 1 continued

Domain	Sec.	Papers	Key Layers	Primary Findings and Headline Figures
Global Systemic Risks	9	43	Cross-border banking and asset positions, sovereign bank nexus, overlapping portfolios and price-mediated feedbacks, information spillovers (mean, volatility, tail), policy and institutional channels	Single-channel models understate systemic risk and overstate stability margins. Coupling is often superadditive (i.e. the coupled-layer impact exceeds the aggregate impact), and systemic importance varies by channel, horizon, and regime, so aggregation can misclassify who matters. Single-layer exposure analysis understates total systemic risk by up to 90% [31]. Expected systemic losses rise by up to 4× post versus pre Global Financial Crisis (GFC) (2008 to 2009) [31]. Critical leverage (single-channel vs. coupled channels) is overstated by 45% to 300% [32], and omitting the overlapping-portfolio layer misses up to 50% of total systemic risk [33]. Average underestimation of systemic risk levels of large banks is 267%, peaking at 500% (multilayer feedback-based measure relative to baseline DebtRank (no bank–firm feedback)) [34]. Exact non-additivity: systemic distress risk is 0.0750 in the coupled two-layer system versus 0.0225 when the two layers are analysed separately and summed (an extra 0.0525 attributable to cross-layer coupling) [35]. A multiplex modelling banking, debt, and equity positions classifies about twice as many countries as systemic as any single-layer, using a threshold where cross-layer distress is triggered once cumulative losses across layers exceed 33% of total external assets [36].

Table 2: Summary of Multilayer Network Methods

Principal Methods*	Primary Application Domains	Role in Multilayer Analysis	Study Sample
Propagation and contagion mechanisms: DebtRank-style iterative distress propagation and cascade models, coupled default and fire-sale dynamics, leverage transmission matrices with spectral stability diagnostics, clearing models for payment obligations, including Eisenberg–Noe extensions with price impact, multi-asset obligations, and default-driven exposures	Bank–firm Networks, Interbank Networks, Financial Markets, Trade and Supply Chains, Global Systemic Risks	Run distress propagation or clearing models (solving for realised payments under default and limited liquidity) on coupled layers of exposures or payment networks to estimate systemic losses and, where applicable, identify or rank systemically important nodes or layers. Separate propagation mechanisms across channels and decompose losses by layer to test interaction effects rather than treating layers as simply additive. Enable comparison of single-layer baselines versus coupled multilayer specifications, and report stability margins from eigenvalue or spectral radius diagnostics, including scenario-free stability conditions derived directly from a transmission matrix.	[20, 24–26, 31–34, 37]
Dependence, spillovers, and connectedness: Time series connectedness and spillover networks, Diebold–Yilmaz spillovers using forecast error variance decomposition (FEVD), vector autoregression (VAR), wavelet and frequency domain connectedness, quantile and tail sensitive directionality and connectedness, tail-risk designs including Conditional Autoregressive Value at Risk (CAViaR)	Corporate Networks, Interbank Networks, Financial Markets, Global Systemic Risks	Build directed connectedness networks from time series by estimating how shocks to one node contribute to the forecast variance or tail risk of others. Results are stacked into layers by channel (returns, volatility, tails) and by horizon or frequency band. Outputs layer-specific spillover matrices and summary measures that identify net transmitters and receivers, separate within-market from cross-market transmission, and support regime and event comparisons without collapsing channels into a single overlay. Where the designs allow, spillovers are separated into contemporaneous versus lagged components, and similarity of spillover patterns across horizons is tracked over time as a diagnostic for structural change. Quantile and tail-sensitive variants focus on extreme outcomes, so they reveal crisis spillovers that average linear specifications can understate.	[38–49]

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Table 2 continued

Principal Methods*	**Primary Application Domains**	**Role in Multilayer Analysis**	**Study Sample**
Regression, attribution, and predictive outcome linkage: Outcome and driver attribution models linking multiplex structure and layer-specific measures to observed behaviour or risk outcomes, including cross-layer explanatory regressions, driver and regime attribution, and prediction or early warning designs using multiplex features	Corporate Networks, Financial Markets, Global Systemic Risks	Link multilayer structure to observable outcomes or drivers rather than only describing topology. Use regressions and related attribution designs to test whether specific layers (for example ownership, governance, information ties, or risk channel layers) explain co-movement, firm outcomes, or systemic risk proxies after controls. In connectedness settings, relates shifts in contemporaneous versus lagged spillovers, and horizon-specific connectedness, to external drivers to support interpretation and monitoring. In prediction settings, use multiplex features or information layers to improve early warning relative to price only or single-layer baselines.	[21, 40, 50–55]
Structure, centrality, and reducibility: Multiplex structure and roles, node and layer centralities including eigenvector, betweenness, multiplex PageRank and related multiplex centralities, mesoscale structure including core–periphery and stochastic block models, layer non-redundancy tests via structural reducibility using von Neumann entropy, compact multiplex descriptors including AOD, ACS, and NCC	All domains	Identify which nodes and layers are structurally pivotal, and test whether layers add non-redundant information beyond an aggregate overlay. Use multiplex centralities and community, stochastic block models, or core structure to rank institutions, firms, or countries within and across layers, and to identify cross-layer bridges and conduit roles, so that 'actors' that are peripheral in one channel but central in another are not missed. Distinguishe size from structural position where the evidence supports it, and tracks how rankings, participation, and community structure change by layer, horizon, and regime. Add mesoscale and higher order diagnostics including compact multiplex metrics, including AOD, ACS, and NCC, to monitor cross-layer participation, overlap, and concentration over time, and topological diagnostics (e.g. Betti numbers for cycle detection) where cycle structure signals feedback potential.	[21, 27, 36, 43, 56–62]

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Table 2 continued

Principal Methods*	Primary Application Domains	Role in Multilayer Analysis	Study Sample
Null models, statistical validation, and hypothesis testing: Degree and strength preserving null models for overlap and testing, maximum entropy benchmarks for centrality, statistically validated link filtering	Bank–firm, Interbank Networks, Financial Markets, Global Systemic Risks	Test whether observed overlap, centrality, or connectivity is more extreme than would be expected from simple constraints alone, by comparing the data to controlled null models that preserve each node's number of links (degree) and total weight (strength). Use degree and strength preserving null models (for example configuration style baselines) to test whether borrower overlap, layer overlap, or mesoscale structure exceeds what local constraints imply. Use maximum entropy benchmarks to assess whether observed centrality rankings can be explained by local degree and strength alone, and to identify residual structure that matters for systemic relevance. Use statistical validation to retain only those links that are unlikely under a null model, yielding sparser, more stable networks for subsequent multilayer comparison and monitoring.	[18, 57, 58, 62, 63]
Backbones and network inference: Backbone filtering and reconstruction, sparse dependence backbones including threshold-filtered networks, PMFG and MST, exposure and overlap construction using holdings-based projections	Interbank Networks, Financial Markets, Global Systemic Risks	Filter dense dependence or correlation layers into sparse, comparable backbones, for example using PMFG and MST, so community structure, centrality rankings, and layer comparisons are less driven by noise and rolling window choice. Then use these filtered representations to compare how multiplex structure changes by layer and over time, and to test whether observed patterns are stable to alternative filtering rules rather than artefacts of the aggregation choice. Where holdings data are available, construct overlap layers by projecting security-level portfolios into interbank links, and compares results across alternative reconstructions when the underlying exposure structure is only partially observed. These preprocessing and inference steps yield sparser, more comparable representations for subsequent layer comparisons and stress designs, while keeping computational costs down.	[29, 30, 43, 64–67]

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Table 2 continued

Principal Methods*	**Primary Application Domains**	**Role in Multilayer Analysis**	**Study Sample**
Input-output flow architectures: MRIO flow multiplex constructions, Leontief and Ghosh inverses for directional decomposition with layer attribution, channel-specific multiplier decompositions, two-sided borrower versus lender exposure separation	Trade and Supply Chains, Interbank Networks, Global Systemic Risks	Build multilayer flow architectures directly from input-output tables, including MRIO constructions that treat countries or sectors as interdependent layers with directed, weighted flows within and between layers, and region-by-sector multiplexes that preserve cross-sector coupling rather than collapsing production into a single aggregate network. Where inverse operators are used, applies Leontief and Ghosh inverses to separate upstream transmission through liability chains from downstream transmission through asset positions, producing layer attributed decompositions that keep instruments and maturities explicit rather than netting channels into an overlay. In trade and investment couplings, use channel-specific multiplier decompositions to separate within-channel transmission from cross-channel spillovers, so trade dynamics are not conflated with investment dynamics. In cross-border banking settings, use two-sided constructions that distinguish borrower side from lender side exposure, so vulnerability and systemic classification are not compressed into a single net position.	[15, 23, 63, 68, 69]
Temporal, horizon, and regime multiplexes: Temporal and horizon multiplex designs, rolling window and time evolving layer stacks, frequency band and wavelet based layers, regime segmented multiplexes, temporal multiplex representations using supra adjacency and evolution matrices, and built from tail-dependence by horizon (quantile coherency), with a tunable coupling parameter linking adjacent time slices	Financial Markets, Global Systemic Risks	Construct layers as rolling windows, frequency bands, or discrete regimes, and where needed use temporal supra-adjacency or evolution matrix representations so that multiplex measures track rewiring and leadership changes rather than assuming a static structure. Enable horizon-specific monitoring by separating short, medium, and long-run connectedness into distinct layers, and support regime comparisons by holding the node set fixed while allowing links and weights to evolve across slices. Where temporal aggregation is used, coupling parameters control how strongly node importance is encouraged to persist across adjacent time slices, allowing the analysis to balance responsiveness against stability in time-varying rankings and community structure. These designs support monitoring because they output time-indexed, layer-specific measures rather than a single collapsed network model.	[39, 40, 42, 43, 45, 59, 70–72]

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Table 2 continued

Principal Methods*	Primary Application Domains	Role in Multilayer Analysis	Study Sample
Composite systemic risk identification: Systemic importance scoring and early warning indicators, multi-attribute ranking on multiplex features including TOPSIS, conditional loss contribution measures including CoVaR and ΔCoVaR on dependency multiplexes, sparse selection and tail vector autoregression indicators using LASSO, and monitoring indices including VTN, NVE, and NCI	Financial Markets, Global Systemic Risks	Convert multiplex position, spillovers, and tail dependence into scalar systemic importance outputs for monitoring and prioritisation. Use multi-attribute ranking on multiplex features, for example TOPSIS, to combine layer-level centralities and spillover indicators into a single ranked list, and use conditional loss designs such as CoVaR and its change, ΔCoVaR, to estimate system loss conditional on institution distress on dependency multiplexes. Where dimensionality is high, sparse selection methods, including LASSO-based tail vector autoregression indicators, extract a small set of network and tail-risk signals into operational monitoring indices. These outputs are then compared against single-layer baselines to show that systemic rankings can differ by channel, and they support layer-aware supervision by reporting which institutions matter, through which layers, and how that assessment changes over time.	[59, 65, 66, 70, 72–75]

Notes. Method families are organised by analytical purpose. Primary domains correspond to the six application domains in Sections 4-9. All citations refer to papers within the 112-paper corpus. Key findings and quantitative magnitudes are reported in Table 1 and Sections 4-9.

**Acronyms:* AOD = average overlap degree; ACS = average connectedness strength; NCC = node cross-layer concentration; VTN = Variance Tail Network; NVE = Network-only Volatility Effect; NCI = Network-wide Contagion Intensity; FEVD = forecast error variance decomposition; CAViaR = Conditional Autoregressive Value at Risk; MRIO = multi-regional input-output; TOPSIS = Technique for Order Preference by Similarity to Ideal Solution; CoVaR = Conditional Value at Risk; LASSO = Least Absolute Shrinkage and Selection Operator; PMFG = Planar Maximally Filtered Graph; MST = Minimum Spanning Tree.

4 Bank-firm Networks

4.1 Scope and corpus

Nine studies examine credit risk transmission between banks and firms, focusing on settings where bank–firm exposures interact with interbank funding, sectoral lending partitions, and corporate cross-shareholdings. Two studies extend this scope to retail lending settings where borrower correlations are represented as multilayer structures without an explicit bank node set, but with the same objective of quantifying how linked exposures can amplify or reallocate credit risk. These studies often report that bank–firm exposures become a major amplifier once coupled with interbank channels, indicating that cross-layer coupling can materially change inferences relative to analysing each channel in isolation.

4.2 Data and layer architecture

Studies in this section mostly treat banks and firms as distinct node sets linked by weighted credit edges, forming a bipartite bank–firm layer. Additional layers are then included, and these differ depending on the research question. Several include an interbank credit layer that shares bank nodes with the bank–firm layer [19, 20], while others add firm cross-shareholdings to capture ownership feedbacks [76, 77]. [18] decomposes the bank–firm bipartite network into industrial sector layers to analyse the structural dependencies in the bank–firm credit market of Spain in 2007. Lending overlaps are tested against null models to determine whether observed connections exceed those expected by chance. The same sectoral logic is applied by [19], who map the Colombian credit system of banks and firms from 2018 to 2020 as a multiplex with layers representing the commercial, housing, and microcredit sectors, together with very short-term unsecured interbank exposures.

An alternative approach employed by [78] constructs a multiplex from distributional moments of intraday returns that links banks, insurers, and energy firms using realised volatility, skewness, and kurtosis. The layers therefore represent ex-post market moments rather than balance sheet credit exposures. A complementary diagnostic study [77] proposes a source attribution approach that uses degree-weighted node information in a multilayer propagation setting. The method uses a stylised three-layered bank–firm network comprising an interbank layer, a bank–firm layer, and a firm cross-shareholding layer. While the study does not use real data, it demonstrates a method for identifying the source of risk under conditions of incomplete observation. [79] differs from the standard bipartite construction. Their framework combines an interbank layer and an inter-firm layer, with cross-layer links between banks and firms, to study counterparty credit risk contagion that can circulate between firm enterprises and banks. This construction is illustrated in Figure 4.

Two complementary retail lending studies build borrower level multilayer networks from agricultural loan records, rather than starting from a bank–firm exposure graph [80, 81]. Unlike the preceding bank–firm designs, these studies keep banks implicit and represent borrower correlations through shared product and geography ties. They use 15 years of lending data for a Latin American country and construct a rolling sequence of multilayer networks from loans granted within each five year window. Each network is organised around a common set of borrower-level observations, implemented as borrower or loan nodes, depending on the paper, and two bipartite layers: a product layer linking the common nodes to crop product nodes, and a geography layer linking the common nodes to district and area nodes. The common nodes are linked to themselves across layers via interlayer links, enabling diffusion across channels rather than within channel analysis only.

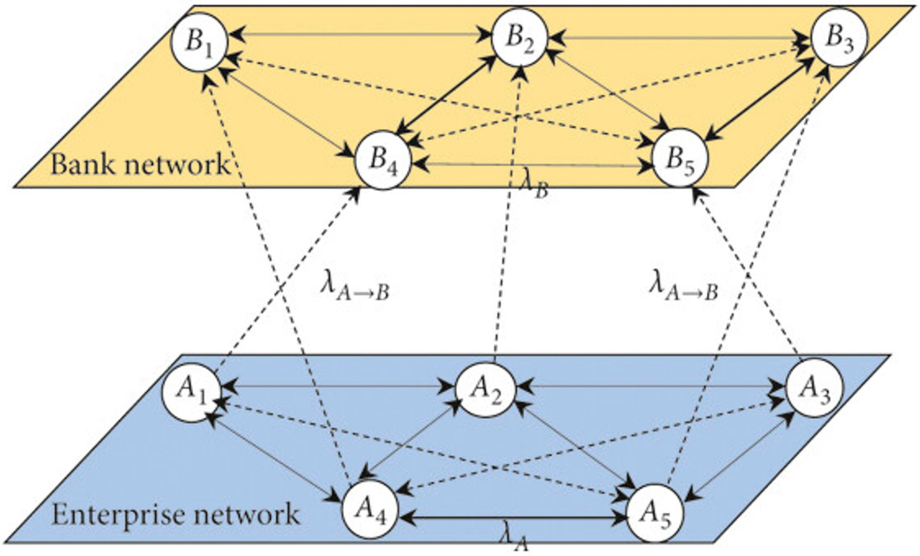

Fig. 4: Schematic of a double-layer network of bank-enterprise counterparty credit risk contagion showing the credit risk transmission path of bank-enterprise counterparties. A state node of the enterprise network has a credit association with the bank network which can infect a healthy status node of the bank network with a probability of $\lambda_{A \longrightarrow B}$ where $0 < \lambda_{A \longrightarrow B} < 1$ and accelerate or cause its default. (Figure reproduced from [79] under Creative Commons Attribution 4.0 International License and published in Complexity, Volume: 2020, Issue: 1, First published: 30 October 2020, DOI: (10.1155/2020/3690848))

4.3 Methods, in brief

Common methods include: simulation models that capture balance sheet feedback; DebtRank, an iterative distress propagation metric used to translate exposures into implied equity erosion under stated assumptions; and null models that test whether observed borrower overlap is structural rather than due to chance.

Two methodological families recur in the bank–firm network studies. The first simulates multilayer contagion on stylised networks in order to study thresholds and cascade sizes when firm, bank–firm, and interbank layers interact; these designs vary capital, degree, coupling, and behavioural rules to isolate mechanisms [20, 76, 79]. The second family builds empirical multiplexes from available data. In a Spanish study [18], lending overlap is tested against degree-preserving and strength-preserving null models, that is, randomised networks constructed to retain key connectivity and weight constraints in the original data. A Colombian study [19] applies multilayer DebtRank to quantify shocks and vulnerabilities, showing how a shock to one node can erode aggregate equity through network links as distress passes to creditors.

To translate a borrower network structure into predictors for credit scoring, [80] introduces a personalised multilayer PageRank diffusion design to track how default exposure evolves across time in the product and geography layers, producing time-indexed risk signals for product and district nodes rather than treating the network as static. The 2021 complementary paper [81] builds directly on this same two-layer bipartite architecture and extends it into a credit risk prediction framework by computing personalised multilayer PageRank exposure scores with known defaulters as the source of influence, then extracting network derived variables for use in supervised credit scoring models benchmarked against non network and single-layer alternatives.

A related diagnostics contribution [77] develops diagnostics for source attribution during cascades by using DebtRank as the propagation engine to generate cascade snapshots for evaluating a label-propagation source-identification, or LPSI, method. This degree-weighted label-propagation algorithm works by passing labels between neighbouring nodes, where each label represents that neighbour's best guess of where the shock originated, with updates weighted by a node's number of connections. Accuracy declines when observability is low (i.e., few node states are visible) or when the true origin is a hub (a high degree node), because many transmission paths can fit the observed cascade [77].

4.4 Mechanisms and thresholds

Across the bank–firm studies, coupling layers amplifies risk primarily through three mechanisms: common borrower exposures, short-term funding feedback, and behavioural credit contraction. Joint-exposure amplification occurs when multiple banks lend to the same firms, which creates bridge paths from firm-related layers, including bank–firm lending and inter-firm exposures, into the interbank layer. Even modest firm shocks can generate simultaneous equity hits at several lenders, weakening capital ratios, reducing funding capacity, and opening further propagation paths. Models with only interbank links therefore understate the risk of system failure because they exclude bridge paths.

[20] demonstrates the threshold shift due to explicit layer coupling in the simplest possible way. In their calibration, an equity ratio of about 10% is sufficient to prevent a full systemic breakdown when distress transmits only through bank–firm connections. After adding an interbank contagion channel, the updated stability requirement rises to

11%. Interpreted as a single-layer understatement, analysing the bank–firm layer in isolation understates the critical equity ratio required for stability by about one percentage point, which is roughly a 9% relative shortfall against the coupled benchmark.

Dynamic funding feedback intensifies vulnerability through short-term liquidity flows, rollover risk, and recovery dynamics on early repayments. In the model setting of [76], early repayments drain borrower liquidity whilst lenders reduce short-term funding. This bidirectional bank–firm feedback creates a loop via which losses propagate within and across layers, amplifying systemic risk. Firm distress weakens banks, those banks restrict credit, and credit restriction accelerates further firm failures. In this loop, thresholds for contagion and system stability then depend on leverage, initial shock size, business interconnectedness and resilience, with structure and behaviour combining to set regime boundaries [79]. A market-based multiplex of realised moments corroborates this pattern using a different approach. [78] demonstrates that banks are net transmitters on average, insurers and energy firms often net receivers, and roles can reverse in jump and tail episodes, which signals regime shifts and amplification through cross-layer transmission rather than simple linear increases in stress and systemic risk.

In borrower-centred retail lending multilayer designs, amplification arises through correlated borrower exposures rather than explicit bank balance sheet feedback. Default influence diffuses through shared product and shared geography ties, and borrower risk is higher when borrowers are closely connected to previously defaulted borrowers in either layer, whereas high connectivity on its own need not imply higher risk [80, 81].

4.5 Findings and quantitative benchmarks

In stylised multiplex simulations, interbank credit on its own produces limited amplification, whereas incorporating bank–firm exposures generates larger cascades that can, under some conditions, lead to systemic failure. [20] demonstrates that, as a result of firm defaults, bank defaults start to emerge once the proportion of bank loans to firms reaches about 15% of bank external assets under a minimum capital requirement set to 6%. This threshold is specific to the study's calibration and serves as an illustration of how coupled channels can generate tipping effects. Mechanistically, the 15% trigger arises from joint borrower exposures that synchronise equity hits across several lenders when a firm is shocked. The empirical question is whether such overlap is pervasive in real data, a question addressed by [18]. This study analyses the Spanish bank–firm credit market (2007), and finds that borrower portfolio overlaps are far larger than expected under standard random-chance null models. Across 1,770 sector-pair overlaps, about 96% show statistically significant positive overlap under a simple random graph null. Under degree-preserving and strength-preserving null models, the share remains substantial, ranging from 63.89% under the weighted configuration model to 41.46% under the enhanced configuration model. This demonstrates that common exposures are structural rather than merely coincidental, indicating that banks systematically concentrate their lending across the same combinations of sectors rather than diversifying independently. This allows sector-specific shocks to hit many institutions at once even if interbank markets remain relatively calm. Given that this overlap appears structural, the bank–firm layer tends to dominate realised loss propagation, as [19] demonstrates for Colombia. Using multilayer DebtRank, commercial credit is identified as the dominant channel for equity loss, whilst the very short-term unsecured interbank layer contributes little once liquidity in that market contracts sharply, for example during COVID-19. In the 2018 model configuration, the maximum impact from a single high-exposure commercial firm default could, through network propagation, erode around 84% of aggregate bank equity, falling only slightly in 2019 and 2020.

Given these structural preconditions and realised impacts, the next question concerns which behavioural and structural settings push the system across loss thresholds. In three-layer simulations that include short-term funding flows, recovery rules, and cross-shareholdings, systemic risk increases as early repayments rise, cross-shareholdings deepen, and the short-term funding market remains active. Both very sparse and very dense network structures amplify losses relative to moderate density, and the effect is muted when the early-repayment fraction is below about 0.30 [76]. In the coupled bank–firm dynamics, contagion thresholds rise with risk management capacity and information processing and fall with leverage, initial shock size, and business interconnectedness. These relationships identify the behavioural levers that move the system between regimes [79].

Analysis of the realised-moment multiplex shows that crisis episodes strengthen cross-layer connectivity and increase multilayer interconnectedness, indicating structural shifts in propagation during stress periods [78]. In the retail lending setting, multilayer diffusion scores provide time indexed risk signals that move more sharply than spot default rates, with default rates lagging network based risk signals at the product district level, supporting early warning use in monitoring [80]. In the follow on prediction design, an extensive evaluation finds that network derived variables are helpful for predicting default, and that proximity to previously defaulted borrowers is the key risk relevant aspect of connectivity, rather than connectivity per se [81]. Because propagation can be large, an important operational question is whether the origin of a cascade can be located quickly enough for intervention. Addressing this question, [77] shows that cascade source identification in bank–firm multiplexes has practical detection limits. To achieve higher accuracy, a degree-aware variant of the label-propagation method weights updates by a node's degree so high-degree lenders or borrowers exert more influence. This variant outperforms the baseline across 100 independent simulations on synthetic bank–firm data, where accuracy is measured by correctly recovering the true source node. Performance depends mainly on node observability, that is, the share of nodes whose distress states are visible. Detection is hardest when the true source is a high-degree or large-asset node, and easiest when the source has low degree and small balance sheet size.

4.6 Implications

Under comparable samples and assumptions, coupled multilayer specifications deliver larger losses than single-layer baselines, although propagation magnitudes vary by dataset and model design. Researchers, risk managers, and regulatory supervisors should preserve the bank–firm layer explicitly and estimate propagation on the multiplex rather than on an aggregate network. Exposure-level datasets that capture sectoral lending overlaps and cross-shareholdings reveal the joint borrower structure that drives amplification, with the Spanish study showing that such tests are feasible with standard supervisory collections [18]. Stress testing should incorporate multilayer tools such as extended DebtRank calibrated to observed structure, and scenarios should include short-term funding behaviour, rollover risk, recovery ratios, and sensitivity to average degree where relevant [19, 76]. Liquidity surveillance deserves particular attention, since early repayment behaviour and short-term funding dynamics can shift the system between regimes in the coupled simulations [76]. Diagnostics that attempt to locate the source of a cascade can support earlier intervention, although attribution performance depends on observability and degrades when shocks originate at hubs because hubs lie on many plausible paths [77]. Where exposure data are limited, higher equity buffers are a prudent offset to model risk and measurement error, which is consistent with the stylised simulations showing that higher capital requirements prevent collapse when the bank–firm layer is active [20].

Stress testing oriented propagation tools, such as DebtRank on bank–firm multiplexes, can be complemented by borrower centred multilayer PageRank diffusion scores that turn shared product and geography ties into operational credit risk signals, spanning monitoring and prediction [80, 81].

4.7 Limitations and future directions

Design and coverage constraints limit how far these findings generalise beyond the studied settings. Several simulations are intentionally stylised or fix behaviours to isolate mechanisms. Examples include topology-driven networks without country calibration or clustering; a two-layer diffusion design limited to product and geography layers, without an explicit bank node set or contract-level loan dynamics [80, 81]; three-layer simulations without explicit interest-rate dynamics, leverage management, or policy reaction functions [20, 76, 79]. Results can also depend on window and horizon choices, including whether influence is measured over one year versus five years, and both retail lending designs are evaluated in a single agricultural lending setting, so transferability to other retail portfolios and to bank-level stress testing remains to be demonstrated [80, 81].

Empirical multiplexes are narrow in time or scope. The Spanish study only covers a single year (2007) and analyses projected bank–bank and sector–sector networks from the bipartite data [18]. The Colombian study maps three retail credit layers plus very short-term unsecured interbank exposures, with measured impacts falling as that market contracts, and omits securities cross-holdings and foreign exchange links [19]. The realised moment multiplex covers a small set of Chinese institutions and does not connect market moments back to credit, ownership, or funding layers [78]. The diagnostic algorithm is validated on stylised data and needs testing on larger real datasets under more complex propagation patterns, including variable observability [77]. These limits suggest caution when moving beyond the studied samples, even though the qualitative mechanisms recur.

These gaps motivate several clear directions for future work. Calibrating topology-driven models to data and adding richer structure, including clustering and higher-order features, would test the strength of mechanisms and refine thresholds and paths [20]. Preserving bipartite structure, extending temporal coverage beyond a single year, and widening exposures to include securities cross-holdings and foreign exchange links would reduce bias induced by one-mode projections and broaden scope [18, 19]. Adding explicit leverage, short-term interest-rate dynamics, and policy intervention channels would increase behavioural realism, and enlarging the agent set beyond banks and firms would connect the moment-based findings to balance sheet propagation [76, 78, 79]. Validating source tracing on larger real datasets and adapting it to bank runs and leverage feedbacks would move diagnostics toward operational use [77].

Despite these limitations, the studies point in a consistent direction. Once bank–firm credit is coupled with interbank funding or other layers, amplification is dominated by joint exposures and short-term liquidity behaviour rather than by interbank credit in isolation.

5 Corporate Networks

5.1 Scope and corpus

The six studies in this section examine how corporate ownership, board interlocks, investor ties, equity returns, supply chains, energy sector links, and tax treaty structures shape network topology, dynamics, and behaviour. Representing these relations as distinct but interconnected layers reveals transmission channels that are obscured in single-layer overlays. Within this scope, cross-layer amplification becomes apparent once production networks are coupled to financial exposures. When supply chains are linked to bank credit, modelled losses can increase substantially relative to bank-only estimates, as stress propagates and intensifies across layers.

5.2 Data and layer architecture

Corporate multiplex constructions in this section fall into three categories. First, corporate control and information multiplexes combine governance and control layers, ownership links, board interlocks, and collaboration ties, and, in some designs, investor ties. These are sometimes paired with a market co-movement layer derived from equity return correlations, allowing tests of whether formal corporate relations help explain firm share price dynamics [21]. Figure 5 illustrates these concepts. Within this category, institutional investor network layers represent social relationships, common activities, and organisational proximity among institutions, then link those investors to the firms they invest in. Constructed using colleague ties, alumni links, parent-subsidiary relations, and common-activity ties, the resulting multiplex is used to study how investor connectedness correlates with corporate governance and earnings outcomes [50].

Second, production and finance layer-coupling designs link real-economy production layers and supply-chain links between firms to bank credit exposures, enabling simulation of shock propagation from firm distress into the supply chain and onward to bank balance sheets [22].

Third, market-based dependence multiplexes constructed using returns, volatility, and tail-dependence layers allow for analysis of static and dynamic networks to study topological network changes, risk contagion patterns, and structural stability during volatility episodes in the underlying asset price [44, 82]. A specialised cross-border extension combines ownership and corporate control layers with a withholding tax network to identify sink and conduit tax jurisdictions and sectoral concentration in tax-treaty-based value flows and investment positions [83].

These multilayer architectures support three inference tasks. They test whether layers are reducible to an aggregated network overlay, track how transmission patterns change across market conditions, and quantify risk amplification when supply links are coupled to financial exposures.

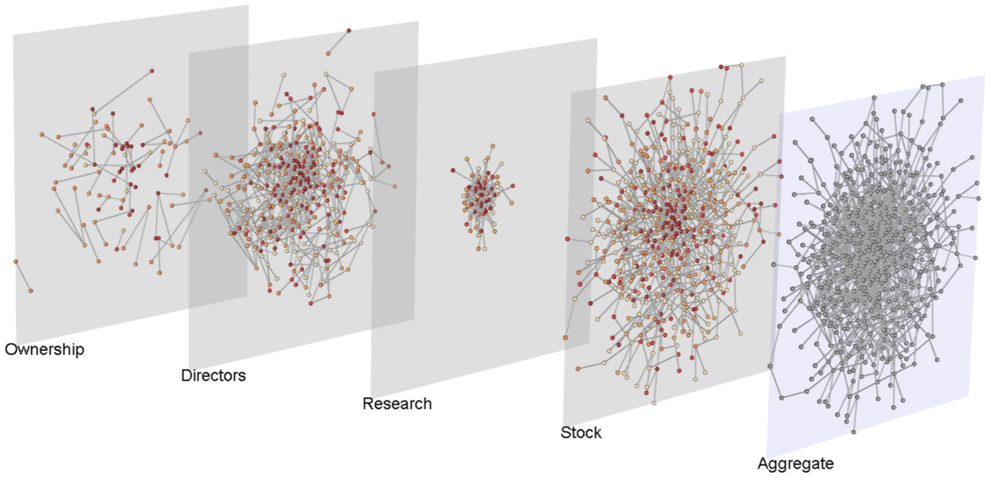

Fig. 5: Multiplex network of listed German companies showing: cross-stockholding ownership network, joint board directors network, research interactions, minimum spanning tree of stock correlations, and the aggregate. We show a multiplex layout; the position of nodes is the same in all layers, but isolated nodes in a layer are not shown. Nodes are coloured by their MultiRank centrality in the multiplex. The visualisation illustrates clearly that these interactions have different structures. (Figure reproduced from [21] under Creative Commons Attribution 3.0 International License)

5.3 Methods, in brief

The methods employed in the six studies can be grouped into three analytical approaches. First, information retention tests ask whether layers can be collapsed without loss. One study tests structural reducibility by comparing the full multiplex with its single-layer aggregated overlay using von Neumann entropy, a measure of structural information content [21]. The authors show that ownership, board interlocks, research ties, and stock-correlation layers are not redundant; aggregating them results in a loss of information that is preserved in the multiplex.

Second, regression designs relate network layers to observable outcomes. One study links equity return correlations to corporate ownership ties, director connectedness, and research interactions using regression, estimating each layer's contribution to observed share price co-movement [21]. Another uses regression to relate institutional investor multiplex connectivity to firm-level earnings management, with results consistent with governance improvements operating through a credible exit threat rather than direct intervention in firm operations [50].

Third, state-dependent transmission is tracked. One study uses rolling windows that combine Diebold–Yilmaz (DY) spillover matrices, built from forecast-error variance decompositions, with Granger direction tests to construct return, volatility, and extreme-risk layers [44]. Another separates normal co-movement from upper-tail and lower-tail dependence using MST and copula functions (statistical models of joint dependence) so links can be attributed to market expansion or contraction [82]. Supply-chain contagion is modelled by coupling a national firm-level production network to bank exposures, and testing both idiosyncratic firm failures and aggregate shock scenarios, with propagation mapped to bank equity using a weighted bank–firm table of credit exposures [22]. Firm-level losses are computed using a generalised Leontief production function and then transmitted to banks via loan exposures, yielding amplified bank risk metrics under supply-chain contagion.

5.4 Mechanisms and findings

Study results are synthesised by the specific mechanism studied: first energy sector multiplexes, then real-economy to bank transmission via supply links, and finally cross-border routing via tax treaties.

Energy sector dynamics illustrate heterogeneity in network structure and layer-specific transmission risk, with the dominant channel contingent on the layer definition. In addition, market stress appears to reshape cross-layer structure. One study finds that in a three-layer spillover network built from daily returns, intraday volatility, and Value at Risk (VaR)-based extreme risk, the volatility layer is the most connected, with the highest average node degree, while the extreme risk layer is the least connected [44]. Using a tail-dependence multilayer framework, another study separates normal dependence from upper-tail and lower-tail dependence and uses centrality measures to track connectedness across states, showing that firms tend to be more interconnected during calm periods and less interconnected during market downturns. This pattern implies that interdependence reweights across layers as market conditions change, with regionally clustered contagion acting as centres of risk transmission [82]. At the system level, stress episodes such as Brexit, trade tensions between the United States (US) and China, and the COVID-19 pandemic are associated with rising system-wide connectedness and a declining unique edge ratio (UER), defined as the share of edges that remain layer-specific, implying greater cross-layer overlap and weaker diversification across channels [44].

Consistent with this, the multiplex corporate interaction study uses centrality measures to show that the full multiplex is more informative than its layer-aggregated overlay, because each layer conveys different structural information, i.e., aggregation suppresses important information. The study also reports an association between multiplex centrality and firm performance [21].

Supply-chain propagation illustrates the scale of real-economy amplification, with a three-stage mechanism observed in a calibration using Hungarian administrative data [22]. Firm failure or a cut in output reduces production and sales, eroding the liquidity of affected firms. These shortfalls then travel along supplier and customer links, affecting their ability to repay bank loans, before finally reaching banks and amplifying bank risk metrics under supply-chain contagion. A narrow set of tightly connected firms, particularly in infrastructure and network sectors, drives a large share of simulated losses. When supply-chain contagion is added to bank-only risk models, Expected Loss (EL) rises by about 5.2×, VaR (a loss quantile) by 6.7×, and Expected Shortfall (the average loss beyond that quantile) by 4.4× on average. These magnitudes, resulting from running 10,000 initial shock scenarios and averaged across 20 banks, are sample-specific rather than universal, but they indicate that bank-only metrics understate both expected and tail losses [22].

In investor-interaction multiplexes, stronger multiplex connectivity among institutional investors is associated with reduced earnings management, an effect that operates primarily through the credible threat of exit rather than via direct intervention [50]. Using a difference-in-differences design (comparing treated and control groups before and after intervention) and the Heckman two-stage model, this effect is shown to remain stable even after adjusting for variable measurements and sample-selection bias issues.

Separately, a tax-treaty study combines a withholding tax network with firm-ownership layers and uses multilayer centrality measures to identify the locations and sectors of conduit firms [83]. Treaty shopping, that is routing investments via conduit firms and jurisdictions to exploit favourable treaty terms, is shown to be concentrated in a small group of locations, led by the Netherlands, Luxembourg, and the United Kingdom (UK), and in a small set of sectors, mainly financial services, insurance, and wholesale and retail trade. This pattern indicates that combining ownership flow intensity with withholding tax advantage yields a ranking in which treaty shopping relevance is dominated by a small set of high multilayer centrality conduits.

5.5 Implications

Supervisory authorities, researchers, and practitioners should keep corporate layers separate in their models, then test how they link to supply-chain networks and financial exposures. Targeted liquidity facilities directed to solvent but at-risk firms, such as working capital lines, may reduce banking losses in supply-chain scenarios, illustrating how real-economy links within multilayer frameworks can be used to design more targeted firm-level mitigation measures [22]. Sectoral stress testing that combines volatility and extreme-risk layers for large energy suppliers would align with common supervisory practice in bank stress testing for an energy sector that appears central to systemic risk transmission [44, 82]. Regarding corporate governance, strengthening credible exit channels and investor communications aligns with the observed association between multiplex investor connectivity and reduced earnings management [50]. On international tax structures, focusing anti-avoidance capacity on identified conduit jurisdictions offers a practical starting point for treaty revision and enforcement, particularly for developing countries with limited administrative resources [83].

5.6 Limitations and future directions

Several constraints temper generalisation of the findings. Time windows used sometimes differ across layers, and handling of missing values is variably documented, making replication difficult [21, 50]. The supply-chain to banking exposures design does not include price information or interbank contagion, so second-round financial feedbacks are not modelled [22]. Further, many studies do not incorporate response mechanisms, and instead assume fixed behaviours. For example, in one study it is assumed that firms have no access to additional equity or liquidity in response to a crisis, leading to simulated loan defaults that may never happen in practice [22]. Some energy sector samples are restricted to a few US-listed firms, which limits how readily the results and modelling choices transfer to other markets. Furthermore, while price-based multilayer networks capture cross-firm transmission, they omit cross-market links [44, 82]. These caveats argue for caution when generalising beyond the studied samples, even when the direction of effects is consistent across papers.

Future work should align time dimensions across layers, use consistent observation windows, and report missing value handling transparently. Future designs should incorporate more realistic firm and bank responses within contagion models [22]. Coverage should be expanded by adding interbank and cross-market links where feasible, and robustness should be strengthened by comparing alternative edge filtering choices, such as backbone filters, and alternative interlayer linking rules. Where possible, researchers should release replication code and data dictionaries. As with most observational network studies, centrality measures and correlation analyses reveal structural patterns but cannot establish causation without stronger identification or experimental variation [21, 44, 50, 82].

In summary, recording corporate relations in separate layers appears to change what can be inferred about behaviour and risk. Entropy tests confirm that layers are not redundant, stress episodes increase overlap across channels, and supply-chain links amplify bank risk beyond bank-only estimates.

6 Global Trade and Supply-Chain Networks

6.1 Scope and corpus

The seven studies in this section examine how trade and supply chain structure is associated with economic dominance and shock propagation in the International Trade Network (ITN) and production networks. Across country, sector, product, and firm ties, these studies investigate how coupling between trade and investment layers, variation in trade volumes, and inter-firm relationships reveal critical network properties. Several studies also examine how trade network architecture evolves and compare shock propagation in trade-only networks versus coupled trade, production, and investment networks.

6.2 Data and layer architecture

Across the seven studies, multilayer architectures follow three recurring designs. The first design, demonstrated by [23], builds the ITN using MRIO data tables as a directed, weighted network of monetary flows in which each node is a country-sector pair and edges represent flows between sectors, occurring both within and across countries. The authors then analyse this network as interdependent subnetworks by applying two alternative partitions: grouping nodes by country to form a national partition, or grouping nodes by industrial sector to form a complementary sectoral partition linking the same sectors across countries.

A second design constructs an explicit multiplex, where layers correspond to industries, sectors, regions, or products. One study uses trade classifications from UN COMTRADE data to construct a two-layer multiplex in which primary and secondary industries form separate weight-heterogeneous layers, representing countries as nodes [24]. Intralayer links are weighted by bilateral trade volumes between countries, while cross-layer coupling links each country's representation across the two layers. This coupling is implemented as complete functional interdependence between layers, so a country's failure in one layer can trigger failure in the other. Figure 6 illustrates the schematic example of this multilayered trade network. At a regional scale, [15] uses a national MRIO dataset to build a region-by-sector multiplex that connects 115 US regions (nodes) and 37 economic sectors (layers). Links are weighted by the monetary flow of goods and services both within layers (intralayer) and between layers (interlayer). Focusing on time-resolved global flows, [84] employ the World Input–Output Database (WIOD) to build a dataset of monetary flows across industries and countries covering 43 countries and 56 industries from 2000–2014. These flows are encoded into a weighted, directed multilayer network where each industry is represented as a layer, each country appears as a node in each layer, and edges capture both intra-industry and cross-industry transactions (from sellers to buyers) that together map the full structure of global value chains. At a finer product-level resolution, [85] uses COMTRADE data comprising 261 countries and 786 products (categories) from 1976 to 2014, to construct a weighted, directed multiplex interpretation of the international trading system. By creating a bilateral trade network of each product within its own layer, with link weights representing export dollar values, [85] reveals product complexity, transnational trading relations, and product specialisation patterns.

The third design introduces cross-domain or cross-tier coupling, constructing a multilayer network that explicitly links trade to other domains, such as investment positions or firm supply chain tiers. For example, in a study focused on the global supply chain in the medical equipment sector, the authors assemble a five-tier multilayer supply chain network from public filings and financial records [86]. Using General Systems Theory, the study decomposes the global medical equipment supply chain into five supplier tiers, analysed at four resolutions: firm, industry, country by industry, and country. In another study, a two-layer multiplex is built with the same country nodes in both layers [68]. Each layer encodes a specific economic relation: trade flows and portfolio investment positions. Cross-layer coupling is introduced via estimated pass-through relationships between trade and investment variables at the country level, to analyse joint shock transmission across the trade–investment multiplex.

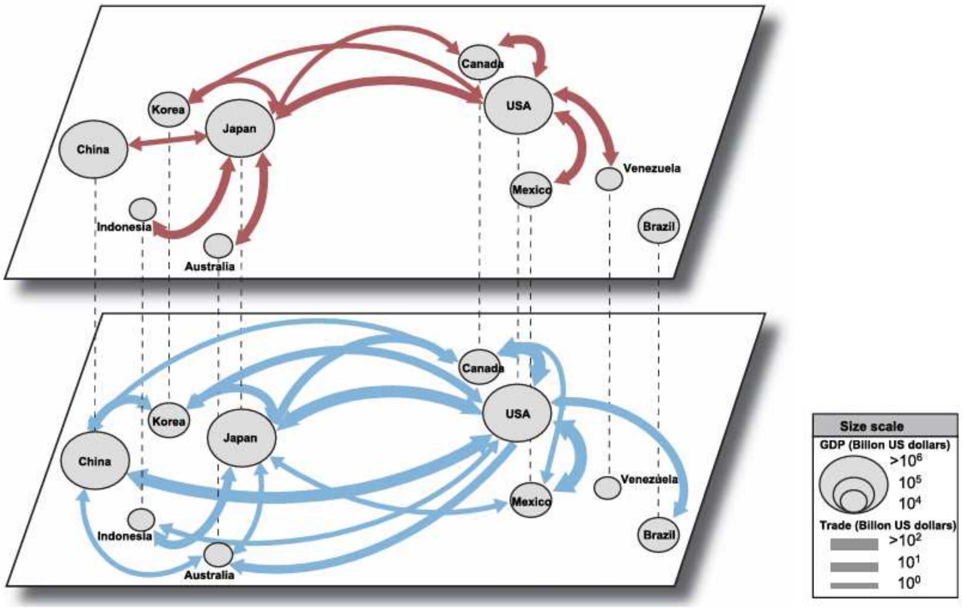

Fig. 6: Schematic example of the multiplex global trade network of 10 countries. The first layer represents the primary industry goods sector (red arrows) and the second layer the secondary industry goods sector (blue arrows). Only those trading relations above 5 billion US dollars were selected as links for visibility. Each node's size is scaled as its gross domestic product (GDP) volume. (Figure reproduced from [24] under Creative Commons Attribution 4.0 International License)

6.3 Methods, in brief

Methods in this domain fall into three tasks: detecting modular structure, simulating cascade dynamics under coupling, and measuring hierarchy or concentration.

Treating the ITN as a network of interdependent subnetworks, [23] compare a country partition and a sector partition with a data-driven community partition. Modularity and variation of information are used to evaluate partition structure and similarity. Weighted Hamming distance tracks year-to-year structural change, and robustness is assessed by normalising weights by annual global trade volume and by a constant link density construction. Finally, cross-betweenness centrality, which measures shortest-path bridging, identifies nodes that connect subnetworks along shortest paths.

For cascades on the ITN, simulations assume full interdependence between layers and examine how failures propagate within and across them. Threshold parameters compare shock magnitude to node capacity to determine whether collapse occurs. In one design, a country's capacity is set equal to its Gross Domestic Product (GDP) [24]. Following an exogenous collapse of a country node in one layer, failure propagates to the corresponding node in connected layers, resulting in a reduction in trade flows. This can trigger further node collapses if neighbouring countries' trade losses exceed their tolerance threshold (shock absorption capacity measured relative to GDP), thus generating additional rounds of cascades across the trade multiplex [24]. In regional production networks, failure likewise occurs when shocks exceed a node's absorption capacity, with systemic impact measured by avalanche size, quantified both as the fraction of nodes that fail and as the total number of collapsed nodes [15]. In trade–investment multiplexes, country-specific multipliers derived from a coupled macro-economic framework map the size of a country-level shock in one layer to the response in both layers, separating within-channel from cross-channel transmission [68].

For hierarchy and concentration, [85] measure country–product hierarchy by focusing on the nested structure in product-specific trade layers using the Nested Overlap and Decreasing Fill (NODF) index. To focus on the main trading links within each product layer, the authors retain only those bilateral flows that are at least as large as that product's average bilateral flow, and treat these retained flows as present links when computing nestedness. In this setting, nestedness captures whether, for a given product, countries with fewer significant trade partners tend to trade with a subset of the partners of the most connected countries, producing a core–periphery style ordering of partner sets within each product layer.

Complementing nestedness measures, economic dominance is measured using a tensor-based eigenvector centrality that captures both within-industry and cross-industry trade by assigning higher scores to nodes connected to other high-scoring nodes. The inverse participation ratio (IPR) is used to assess how concentrated buyer and seller dominance is, with a higher IPR indicating that economic dominance is held by fewer countries. Buyer and seller networks are analysed separately, using eigenvector centrality, with domestic flows treated distinctly from international flows [84].

6.4 Mechanisms, findings, and quantitative benchmarks

Findings cluster into three themes: partition structure in trade networks, cascade amplification under cross-layer coupling, and hierarchy and visibility across country, product, and firm representations.

Country and sector-based partitions reveal complementary structure that varies over time [23]. Country partitions align closely with inferred communities, whereas sector partitions do not show the same within-group concentration of links. Furthermore, under the weighted modularity statistic, country and data-driven partitions trend downward through the 1990s, while sector-based partitions rise, with an anomaly around 2009. When weights are ignored, modularity trends downward for all partitions. Within economies in 2005, domestic trade volume is dominated by financial services and business activities, whereas foreign trade volume is dominated by electrical and machinery products. Node strength, defined in the study as total inflow plus outflow, increases over time. Link density also rises, with a pronounced dip in 2009, while weighted Hamming distance indicates year-to-year reorganisation under both country and sector partitions [23].

Multilayer frameworks preserve distinct ties rather than collapsing them. When layers interact, cascades become larger and more frequent than in single layers. Cascade sizes are also superadditive, meaning the multiplex cascade size exceeds the sum of single-layer cascade sizes. Using data for the year 2000, a two-layer network is constructed that splits traded goods into primary and secondary industry layers [24]. The study shows why aggregation can be misleading: primary industry goods account for about one fifth of total link weight (\$1.3 trillion versus \$4.9 trillion), yet the primary goods layer drives multiplex cascades disproportionately once coupled with the secondary layer, exemplifying the strength of 'weaker' layers. Because the secondary layer carries nearly four times the total weight of the primary layer, weight dominance is clearly a poor proxy for systemic importance: an aggregated single-layer network calibrated to the same totals can systematically understate both the frequency and the size of cascades. Similar threshold effects appear in regional production multiplexes.

Complementing these findings on cross-layer coupling, [15] demonstrates that 22% of monetary flows occur within sector layers while 78% occur between sector layers, implying that between-sector coupling carries about $3.5\times$ the within-sector flows. Consequently, analyses restricted to single-layer sector networks exclude most of the channels through which shocks can spread beyond the originating sector. Failures remain contained until absorption capacity falls below critical values relative to shocks; beyond this threshold, avalanche size rises quickly. For avalanches exceeding 100 collapsed nodes, the probability varies sharply by sector layer, from 1% in machinery to 62% in government. For all sector layers, the probability of large avalanches, defined as exceeding 10^3 collapsed nodes, ranges from 1% to 95%. The most fragile regions cluster geographically and specialise in food and manufacturing, with services and chemicals showing higher cascade propensity in multiple scenarios [15].

Trade and investment relationships propagate shocks through distinct channels. For large economies, country-specific shock 'multipliers' are largely stable across shock sizes, so systemic impact scales approximately linearly with shock intensity [68]. Multipliers act as scale factors linking an initial shock to the system-wide response. Larger absolute values imply stronger amplification, and negative values imply an opposite signed response. [68] reveals that shock transmission is strongest within each channel (trade and investment), with weaker cross-channel spillovers, especially from investment to trade. The intra-layer multiplier for a trade shock on trade activity is about 4.5 ± 0.5, whereas the trade-to-investment multiplier is -0.6 ± 0.3, indicating that trade shocks can produce an increase in liabilities in the investment layer, perhaps to compensate for the reduction in export revenue, consistent with an offsetting cross-channel effect under a trade shock. Collapsing layers into an aggregate would misattribute these effects and lead to mistargeted interventions, whereas channel-specific monitoring and intervention target the mechanisms that actually carry the shock [68].

Economic dominance, measured by eigenvector centrality in buyer and seller layers, shifts over time [84]. Buyer and seller rankings show an abrupt reversal of leading roles just before the global financial crisis (GFC), with new winners and losers emerging between 2007 and 2008. The IPR drops during the crisis (buyers 2007–2008, sellers 2006–2007), indicating a more homogeneous redistribution of dominance. [84] further establishes that domestic transactions are the main driver of localisation, demonstrated by decomposing the network into international and domestic components and varying the domestic contribution using a control parameter.

At the product level, nestedness (NODF) summarises how strongly a product's trade layer exhibits a core–periphery structure once countries are ordered by number of trading partners [85]. Higher nestedness indicates that countries with relatively fewer significant links tend to connect to a subset of the partners of the most connected countries. Consequently, smaller traders' partner sets are largely contained within those of the core, and direct links among peripheral countries are comparatively rare [85]. In addition, [85] show that China's competitiveness strengthens after 1990 and that the gains are especially pronounced after 2005 in products whose trade layers are more strongly nested.

At the firm level, visibility must extend several tiers to reveal critical dependencies. In global medical equipment, indirect links through software, semiconductors, and automotive inputs emerge only after mapping extends over at least five supplier tiers, demonstrated using clustering-based analysis. The authors use this to motivate five tiers as a practical minimum for supply-chain visibility [86]. The same mapping exercise also shows that small jurisdictions can act as key intermediaries, because brokerage roles do not scale directly with economy size.

6.5 Implications

For policy and practice, the principal message is to preserve multilayer structure when mapping trade and production networks. In intranational supply chains, multilayer structure is fundamental rather than marginal. Within-sector links account for 22% of monetary flow while cross-sector links account for 78%, so single-layer sector networks miss most shock transmission routes [15]. Further, link-weight share should not be used as a proxy for systemic importance when layers interact. Because weak layers can be strategically important, they should not be collapsed into aggregates. Screening or stress tests based solely on link-weight proportions can underestimate systemic risk, even when one layer dominates total weight. Such underestimation increases the risk of inadequate safeguards against catastrophic failure [24].

In MRIO-based trade networks, community structure aligns more closely with country partitions than sector partitions, so monitoring frameworks should incorporate both partitioning approaches [23]. Monitoring absorption-capacity thresholds and partner heterogeneity is essential when assessing shock transmission. Where data permit, linking trade to financial positions clarifies which channels carry a given shock. Joint representations can also change inferences about how disruption travels across the real economy and the financial system [15, 68]. Deep supplier tier mapping is necessary to uncover indirect pathways and intermediary jurisdictions. The evidence in [86] suggests that at least five supplier tiers represent a practical minimum for stable dependency mapping.

6.6 Limitations and future directions

A recurring limitation across these studies is that inference is sensitive to network construction choices, including multilayer design decisions, thresholding, and link-density parameters. Therefore, robustness checks, such as constant link density reconstructions, are useful complements to fixed-threshold networks. Additionally, monetary trade flows do not perfectly correspond to physical trade volumes due to price and exchange rate volatility, which can affect the interpretation of network weights [23].

Input-output statistics may exhibit reporting biases, with domestic data typically being more accurate than international flow data.

Cascade models often use static snapshots and assume uniform coupling between layers, whereas realistic interdependencies are partial and heterogeneous. Most sample windows precede disruptions such as Brexit, COVID-19, the Russia–Ukraine war, and major tariff changes, which limits direct validation against these episodes [15, 24, 68]. Firm-level mapping is constrained by reporting thresholds and is often analysed tier by tier, rather than integrating tiers into a single linked representation with consistent identifiers across levels [86].

Future work should represent partial and heterogeneous interdependencies rather than assuming complete coupling. Researchers should extend temporal coverage to include recent disruptions, enabling event-calibrated validation exercises. They should also integrate firm-tier mapping across layers within consistent observation windows to support triangulation between macro patterns and firm-level evidence.

Overall, the evidence shows that aggregation can misrank systemic importance, and that deeper, coupled representations materially change which nodes and channels appear critical during disruptions.

7 Interbank Networks

7.1 Scope and corpus

Systemic risk propagates through interbank linkages via both direct channels (loans, deposits, derivatives) and indirect channels (common asset holdings, overlapping portfolios). The datasets utilised in many of the papers span European banking groups, Latin American systems, Chinese banks, and samples that include both Islamic and conventional banks. Across twelve studies, indirect price-mediated channels and cross-layer coupling materially alter both propagation dynamics and systemic rankings, revealing transmission channels that aggregated single-layer representations conceal.

7.2 Data and layer architecture

Most studies in this section follow similar architectural principles, differing primarily in data source, number of layers, and the financial items each layer represents. Principally interbank-focused multiplexes are built from financial instrument types, maturities, and exposure categories [87]. Layers are typically constructed from regulatory filings and balance sheets, securities and asset holdings at instrument level, and, in some studies, transaction or market-based data. Direct layers disaggregate the interbank market by financial instrument type, including interbank credit, repo or securities financing, interbank deposits, securities exposures, derivatives, and, where transaction data are available, payment flows [57, 58, 63, 64, 88]. Figures 7 and 8 illustrate these concepts.

Some stylised interbank multiplex designs define layers by liability seniority rather than by instrument class, representing junior and senior claims as distinct layers in which repayment priority differs [89]. This layer choice isolates a contract design dimension, seniority composition, that is usually hidden when exposures are aggregated across claims [89]. Indirect layers capture linkages such as cross-holdings and overlapping portfolios through common asset holdings [26, 58, 64, 90]. Overlapping portfolio layers are constructed from security or asset class holdings projected onto interbank links, which often differ in density from credit and funding layers [26, 58, 64]. Links are weighted and directed where appropriate, and node attributes capture size measures such as total assets or capital [57, 63].

To illustrate, a three-layer bank multiplex is constructed using annual balance sheet data of 41 Chinese commercial banks from 2015 to 2021. The three layers represent interbank lending, cross-shareholding, and overlapping portfolios (common asset holdings), with cross-layer dependencies [90]. A complementary Chinese study constructs a four-layer interbank network with three directed, weighted layers for interbank lending, repo activities, and interbank deposits, plus a directed, weighted indirect layer capturing overlapping portfolios through common asset holdings (proxied by bond holdings), using balance sheet data from 2014 to 2019 [64]. Drawing on European data, [26] uses data extracted from the European Banking Authority to construct an interdependency network composed of 48 banks and 21 asset classes. Moving to the Mexican banking system, [88] uses data from SPEI and regulatory reports available to construct daily transaction and exposure matrices from January 2005 to December 2015. The study initially considers seven separate and interdependent layers but aggregates four into a total exposures layer, producing a four-layer multiplex. The resulting layers comprise securities market transactions, repo transactions, payment flows, and total exposures (the last aggregating interbank deposits and loans, derivatives, foreign exchange transactions, and cross-holdings of securities) [88]. Also in Latin America, a study of the Peruvian banking system constructs a monthly multilayer exposure network for October to December 2019 using a comprehensive dataset provided by the Central Reserve Bank of Peru to build six layers of interbank exposures [25]. The study also constructs an aggregate overlay for comparison to the multiplex, which clarifies what is lost by collapsing layers.

Within specific contexts, such as euro-area securities markets, two directed constructions are distinguished using links that are directed from holder-to-issuer. Because issuer and holder are observed, securities networks can be directed, enabling two complementary constructions: an exposure view (holder to issuer) and a funding view (issuer to holder) [91]. This separation highlights which banks are more reliant on funding from the euro area bank network and which are more exposed to it, and it shows that liquidity risk in funding layers and credit risk in exposure layers can affect banks differently across instrument categories [91].

7.3 Methods, in brief

Empirically, studies combine structural analysis, propagation models, decomposition methods, and techniques for inferring network architecture. Centrality measures such as betweenness and eigenvector centrality are benchmarked against maximum entropy null models that preserve degree and, in weighted settings, strength sequences, to test whether observed importance exceeds what local constraints imply [57]. PageRank identifies banks that are influential through their links to well-connected counterparties, computed layer by layer [25, 58, 63, 90]. Core-periphery analysis separates dense cores from sparse peripheries, with these structures differing substantially across layers

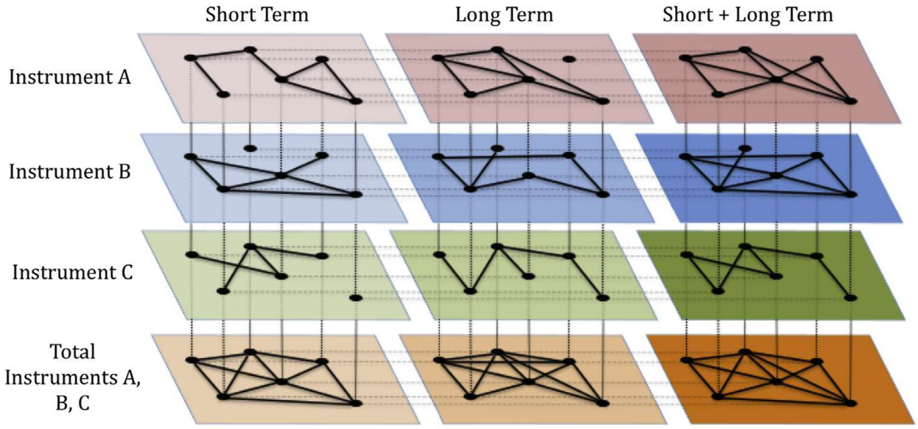

Fig. 7: A stylised representation of a multiplex interbank network, where directionality and link weights have been omitted. Black dots indicate node-aligned banks, thick lines represent intralayer links, and thin lines represent interlayer links. This network displays two aspects: maturity type and financial instrument type. The former aspect is composed of two layers, whereas the latter presents three layers, hence the multiplex network is composed of 6 layers. Maturity and instrument type aggregate networks are also shown. (Figure reprinted from [63], with permission from Elsevier.)

[25, 57, 63, 88]. DebtRank and related cascade models evaluate systemic relevance by layer and in aggregate, with explicit comparisons between multiplex and single-layer outcomes [87, 90]. A complementary cascade approach models interbank lending as a two-layer multiplex of junior and senior loans, with multilevel default states that distinguish failure to repay junior liabilities from failure to repay both junior and senior liabilities [89], then simulates default contagion as a threshold cascade with distinct default states that reflect whether a bank fails to repay junior liabilities only or both junior and senior liabilities. They derive an analytical cascade condition (via the Jacobian of the recursion) and map cascade regions over random network ensembles, then identify an "optimal seniority ratio" that minimises the range of loan densities for which large cascades are likely. Stability is characterised by a cascade condition derived from the multiplex cascade dynamics, which maps the network density regimes in which small shocks can trigger system-wide cascades and how these regimes shift with the seniority mix [89]. Another study combines a default cascade model with a fire-sale spillover model in a unified interdependent framework, in which bank interactions arise through direct cross-holdings and indirect dependency via common external assets outside the banking system [26].

Input–output methods decompose the system-wide balance sheet into instrument and maturity layers. Backward linkages use the Leontief inverse to trace how borrower-side shocks propagate upstream through the liability chain to creditors. Forward linkages use the Ghosh inverse to trace how funding shocks propagate downstream through asset positions [63]. Normalised indices are attributed to specific layers, which

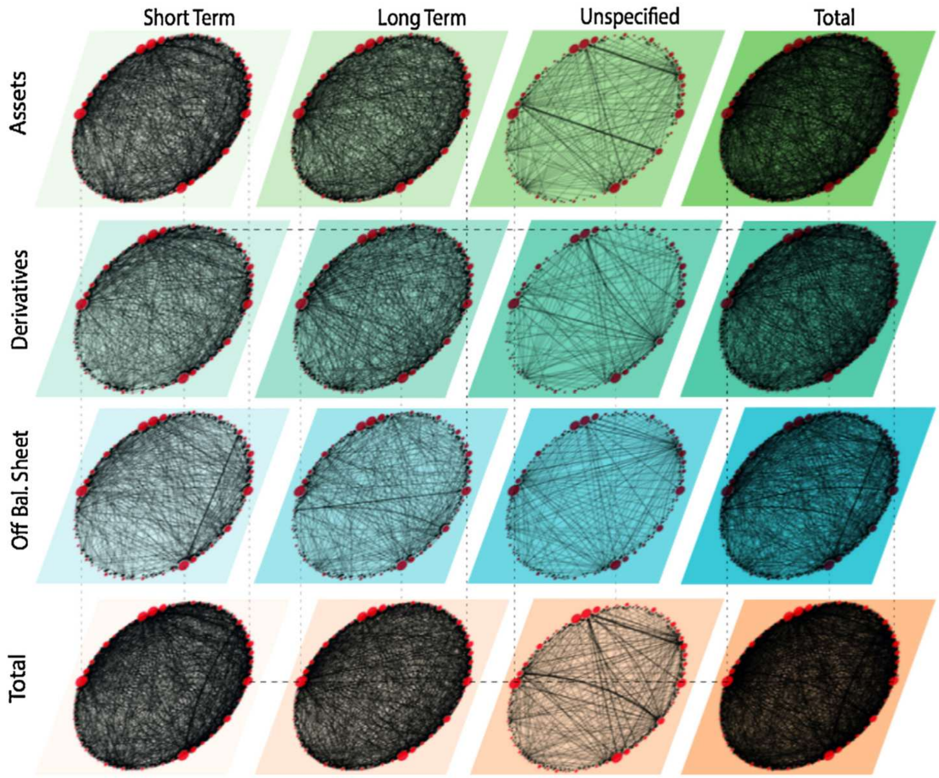

Fig. 8: The multilayer network of large European banks. Node size indicates total assets, link width indicates size of exposure, link direction goes from lender to borrower bank. (Figure reprinted from [63], with permission from Elsevier.)

yields a decomposed systemic footprint for each institution [63]. Stochastic block models and topological data analysis are used to analyse community structure and temporal stability, including the evolution of cycles measured by the first Betti number, a topological measure of the number of independent loops formed [88]. Separately, multilayer Granger causality designs link stock returns, volatility, and extreme-risk layers to study information spillovers within dual banking systems [48].

7.4 Mechanisms, findings, and quantitative benchmarks

Size is informative but not determinative. Balance sheet size is associated with measured centrality in some layers, but the association differs depending on the concept that layers represent, for example maturity and secured versus unsecured layers [57], and by instrument class [58, 90]. Large banks often rank highly across multiple layers, yet rankings are not stable across channels, since some mid-sized institutions are peripheral in one layer but pivotal in another [57, 58]. When systemic importance is defined using multilayer impact measures or balance sheet decomposition by instrument and maturity, size alone is not determinative once the underlying layer structure is respected [63, 90].

Channel architecture sets speed and reach. Overlapping portfolio layers are structurally denser and exhibit shorter intermediation chains than credit layers. When these layers are coupled in a multiplex, cross-layer interactions can amplify losses relative to single-layer representations [90]. In multilayer topological analysis conducted by [58], the overlapping portfolio layer has a smaller diameter in the largest connected component, around two edges, whereas credit, cross-securities, and funding layers have a larger diameter, around four to five edges, indicating a more compact structure for price-mediated channels. Across layers, the majority of nodes belong to the largest connected component: approximately 80 to 90% in credit and cross-securities layers, compared with 64% in the short-term funding layer, and 90% in the overlapping portfolio layer, with remaining nodes forming disconnected components [58]. Consistent with this, the distributions of degree and exposure size are heavy-tailed, meaning that a small set of institutions carry a disproportionate share of potential spillovers [58]. These topological distance differences are consistent with interaction effects once channels are joined, since more compact price-mediated layers can transmit stress through fewer steps than default-driven layers.

Liability structure reshapes cascade regimes. When interbank loans are partitioned into junior and senior layers, systemic fragility depends on the composition of claims, not only on aggregate exposure volume. In a multiplex with senior and junior claims, mixing seniority can shrink the 'cascade window' (the density range where large cascades occur). This window is minimised at an interior seniority ratio rather than at the extremes, hence stability is maximised at an optimal, intermediate seniority ratio [89]. The stabilising seniority mix shifts toward a higher share of senior claims as banks' default thresholds fall, linking liability structure directly to contagion susceptibility, and the baseline setting reports an optimal seniority ratio of roughly 1.79 senior loans per junior loan [89].

Interaction effects are non-additive. The Peruvian case study [25] demonstrates that DebtRank on the combined exposure network exceeds the sum of layer-specific DebtRanks, implying cross-layer interaction effects, so a layer-by-layer assessment understates systemic risk when layers interact. The authors also note that, for some institutions, neglecting the multiplex structure can lead to an underestimation of up to 30% of systemic impact [25]. The maximum DebtRank reported for the monthly sample is around 6.5% of system capital, where DebtRank is defined as the system's final losses relative to capital following the initial default of a bank [25].

China-based evidence similarly indicates that combining direct transaction layers with indirect common asset holdings can produce non-additive amplification, so total systemic risk differs from the sum of layer-specific risks [64]. The study quantifies a non-linear interaction term between layers, which ranges between -0.13 and 0.12 under liquidity shocks, meaning that combining direct transaction layers with common asset holdings can alternate between net amplification and net diversification, rather than producing a monotonic increase in systemic risk [64]. In these designs, the indirect common asset holdings layer can be more extensive than direct interbank transaction layers, and its contribution to systemic risk can rise through time [64].

European stress experiments reinforce the importance of indirect channels: when default cascades are joined with fire sales, indirect losses constitute about 21–24% of total losses, and aggregate vulnerability is around 14–16% of system equity [26]. The interdependency network, driven by indirect dependence via common external asset holdings, is denser than the direct cross-holding network and accounts for the majority of defaults in these experiments [26]. The qualitative hierarchy of channels remains robust across alternative network reconstructions, which points to persistent structural features rather than artefacts of any single inference method.

Bank type and regime matter. In samples that include both conventional and Islamic banks, interconnectedness and vulnerability are regime-dependent and layer-specific. Islamic banks appear more susceptible to real-economy conditions during oil price decline periods [48]. Episodes of elevated spillovers cluster around crises and oil price declines, with extreme-risk layers exhibiting the largest increases, underscoring the value of separating layers when identifying risk transmission and reception. These regime shifts motivate decompositions that identify which channels drive systemic relevance, as the same institution can shift from peripheral to central depending on the active transmission mechanism. Because amplification depends on which institutions carry which channels, bank type and regime differences become policy-relevant rather than descriptive detail [48].

Decomposition exposes where to act. Input–output methods compute backward and forward linkages. When normalised at the system level and decomposed by instrument and maturity, these indices identify institutions that are above average on both measures and show that layer contributions vary markedly across banks. In particular, long-term exposures account for the largest share of backward and forward linkages for most institutions, while short-term and off balance-sheet layers dominate for specific banks [63]. This decomposition helps identify where constraints would bind most strongly, relative to an aggregate overlay that obscures which instruments and maturities drive each bank's systemic footprint [63].

The funding versus exposure view distinction noted earlier shows that a bank can appear central on one side and peripheral on the other, so policy that monitors only one view risks missing the other [91]. Because securities are often traded through and held by non-bank intermediaries such as investment funds, these two network constructions can differ materially, which affects interventions designed using only one of these views [91].

Higher-order structure signals feedback potential. Stochastic block models recover communities with similar linking patterns, and topological data analysis tracks the emergence of cycles via the first Betti number. These tools complement classical centrality by revealing alternative pathways beyond shortest-path routes and by signalling when network architecture is becoming more cyclic, conditions under which static, channel-isolated oversight is most likely to miss compounding feedback routes [88].

7.5 Implications

The Peruvian and Chinese case studies demonstrate that decomposing systemic importance by layer provides the empirical basis for more targeted risk policies, as aggregated analysis understates cross-layer amplification and can miss banks whose influence emerges only through layer interactions [25, 64]. Decomposed backward and forward indices identify instruments and maturities where constraints would bind most tightly [63]. In summary, these results provide strong evidence that risk managers and regulatory supervisors should adopt multilayer frameworks to capture the specific transmission channels that aggregate models miss.

Further, there is strong evidence that centrality varies by layer [57, 58, 90]. In euro area securities layers, banks not classified as global systemically important banks (G-SIBs) can still be pivotal, so systemic ranking cannot be inferred from regulatory classification or balance sheet size alone [58, 91]. Across layers, overlapping portfolio structures tend to be more compact than credit and funding layers, consistent with shorter network distances [58]. Together, these results imply that supervisory conclusions depend on which channels are represented and how they are layered [57, 58, 90].

The result that indirect linkages from common asset holdings can become increasingly important, and that combining linkages can produce non-additive amplification, supports the monitoring of overlapping portfolios alongside direct interbank exposures [64]. The empirical finding that indirect holdings can dominate direct links in determining system impact, together with non-linear amplification across channels, supports closer monitoring of cross-holdings, securitised exposures, and common external asset holdings alongside plain interbank credit [26, 91]. For stress testing, incorporating solvency shocks alongside funding withdrawals, balance sheet contagion, fire-sale spillovers, and price-mediated mechanisms within a multiplex framework alters both loss magnitudes and systemic rankings relative to single-channel designs [26, 64, 90]. Beyond exposure size and counterparty structure, repayment priority also matters, since modelling junior and senior interbank loans as separate layers shows that the seniority mix changes the cascade window and can shrink the parameter region in which large cascades occur [89]. Interpretations of securities networks should state explicitly whether the funding view or the exposure view is used, since the two perspectives can differ materially and neither fully captures the other [91]. Once interventions are targeted to specific instruments and maturities, analysis of higher-order structure becomes necessary because feedback potential depends on whether alternative pathways and loops exist beyond shortest-path routes [88].

7.6 Limitations and future directions

Several methodological limitations appear across the literature. Many influential constructions are scenario-based stress experiments and omit endogenous balance sheet adjustment or policy feedback over multiple periods, which restricts multi-period stress testing [26]. Dynamic multiplexes that allow feedback between layers are therefore a clear next step. Balance sheet granularity and coverage of off-balance-sheet exposures remain limiting in several settings; more detailed data would be informative but is often costly or unavailable [64]. Stress tests and centrality-based measures are not standardised across jurisdictions, and real-time surveillance remains challenging as dimensionality rises. Furthermore, adaptive behavioural responses and regulatory interventions remain largely outside current models, despite their practical influence on incentives and market concentration.

Future work could extend the multiplex designs to include other financial intermediaries such as insurance and investment funds [25], and broaden securities layers beyond the euro area, since current constructions restrict both holder and issuer coverage to euro area entities [91]. Fintech platforms and sovereign balance sheets could similarly be incorporated within fully interdependent networks, and securities, payment, and clearing infrastructures could be embedded within operational workflow models. Finally, those multilayer framework designs that purely focused on direct exposures could incorporate indirect exposures, for example from common asset holdings.

Despite these limitations, the studies have shown that across a variety of in-country banking systems, distinct layers contain non-redundant information, overlapping portfolios transmit stress more quickly than credit links, amplification is non-additive once channels interact, and systemic importance depends on activity type and market context [58, 90]. Together, these patterns support layer-aware supervision and multiplex stress tests that couple default, funding, and price-mediated channels.

8 Financial Markets

8.1 Scope and corpus

Thirty-two studies in this corpus model financial market interdependence by representing assets, time horizons, and risk channels as distinct but coupled layers. Across these designs, three headline patterns recur: volatility layers often dominate return layers during stress episodes; crises shift spillovers towards longer time horizons; and infrastructure concentration creates vulnerabilities that a single-layer overlay can miss. Retaining layers, rather than collapsing them into a single overlay, changes both the inferred structure of financial market dependence and the identification of key transmitters, receivers, and conduits, especially during stress episodes.

8.2 Data and layer architecture

Many financial market multiplexes are built over a common set of securities by stacking multiple dependence measures, such as Pearson, Kendall, partial, or tail dependence, each defining a distinct layer [27]. Beyond dependence layers, designs add modality layers such as returns, realised volatility, and trading volume. Some studies also include risk-specific layers, such as implied variance and the variance risk premium, defined as the difference between implied and realised volatility and commonly interpreted as compensation for bearing volatility risk [39]. This is illustrated in Figure 9.

Layering can also be defined by time horizon or by risk channel. In one study of horizon-based connectedness layering, a multiplex connectedness network in the frequency domain is constructed for 22 stock markets using daily high and low price data from the WIND database, treating short, medium, and long horizons as separate layers to locate where contagion concentrates across the frequency spectrum [38]. In cross-asset settings, spillover multiplexes are also built using a node set spanning bonds, foreign exchange, and equities, while layers separate mean, volatility, and extreme-risk spillovers, so that stress signals need not manifest initially through the mean channel [92]. A related cross-market construction links the crude oil market with G20 equity markets [29]. Using 16 years of daily price data from the Wind database, the study defines three directed spillover layers: return, volatility, and extreme risk, with extreme risk of the G20 stock markets and oil market measured using VaR. Each node represents one of these markets, and connectedness is estimated separately within each layer, which enables comparisons of overlap and layer-specific structure over time [29].

When market infrastructure is the object of study, layers are organised around clearing roles and derivative product classes, for example participation of clearing members and central counterparties (CCPs) in derivative clearing networks, so that cross-layer clearing participation reveals potential propagation routes across financial product clearing markets [62]. Where institutions dominate the mechanism, layers represent market segments or asset classes [56]. Trade repository data can support layer definitions by contract class, for example UK over-the-counter (OTC) derivatives exposures are built as three directed layers, comprising interest rate, credit, and foreign exchange, so that margin-driven liquidity stress can be traced across products that share the same small set of major dealer institutions, allowing liquidity shocks at those dealers to transmit between layers [56].

On the modelling side, multi-asset clearing models treat currencies or assets as layers, allowing obligations in multiple illiquid assets and price impacts to create multiple equilibria and discontinuous stress responses [37]. In this construction, multilayer exposure networks are defined over assets rather than contracts, with each currency or illiquid asset forming its own layer in which obligations are met physically. This layering becomes essential once physical delivery and illiquidity invalidate the assumption that obligations can be settled in a single cash equivalent, which can otherwise misstate losses and feasibility [37].

8.3 Methods, in brief

Method choice in financial market multiplex studies aligns with layer meaning, with different toolkits used for dependence layers, directed spillover layers, and institution or infrastructure layers. Most studies fall into three methodological groups with a smaller subset of studies that complement these empirical approaches, either by fixing layers exogenously or by using structural or numerical multilayer models rather than empirically inferred networks.

First, in *dependence structure* studies, multiplex layers are analysed using overlap and layer uniqueness metrics, often alongside community comparisons across layers and rolling windows [27, 28]. These diagnostics are comparative, testing whether layers are non-redundant, whether communities are robust to construction choices, and whether stress periods alter multiplex organisation in ways that overlays obscure [27, 28, 61].

Because dependence estimation on financial market multiplexes can be noisy, several studies sparsify dense dependence networks before comparison, using statistically validated backbone-based filtering, including the Planar Maximally Filtered Graph (PMFG), the Minimum Spanning Tree (MST), and threshold filtering [27, 29, 67, 93].

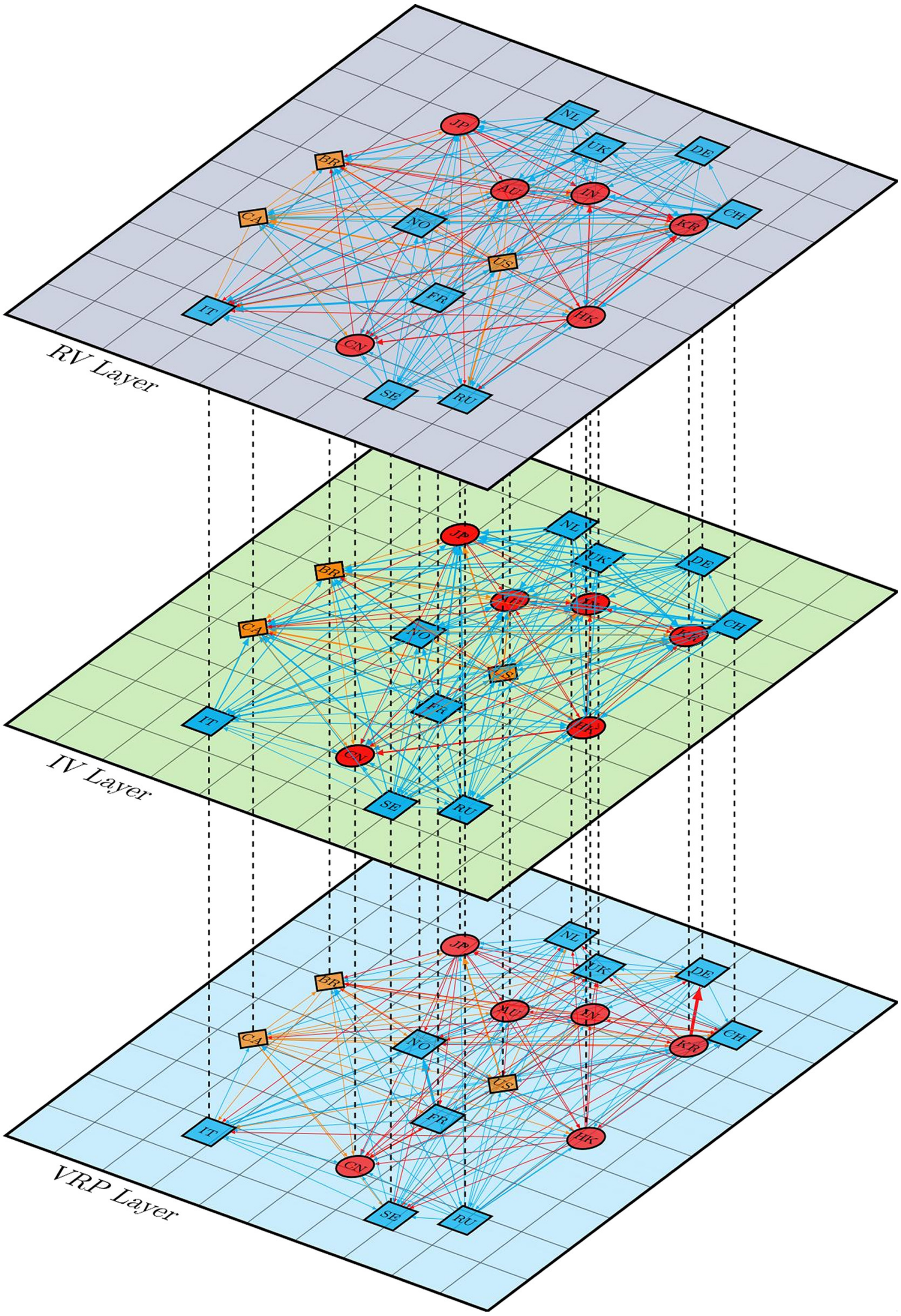

Fig. 9: Multiplex information spillover network showing a realised value (RV) layer, an implied variance (IV) layer, and a variance risk premium (VRP) layer during the full-sample period (19 June 2015 to 25 February 2022). Nodes and edges represent 18 financial markets and volatility spillover effects, respectively. Red circle, blue rectangle, and orange diamond represent regions of Asia-Pacific, Europe, and America, respectively. Directed edges on each layer start from spillover emitters and point to spillover receivers. Edges' colour follows emitters, and the width is proportional to spillover strength. (Figure reprinted from [39], with permission from Elsevier.)

In this approach, layers are compared over time on the resulting sparser graphs rather than on full dependence networks.

Several studies guide threshold selection using global efficiency, defined as the average inverse shortest path length across node pairs, which typically declines as filtering strengthens [30, 94]. In practice, this supports choosing thresholds within a range where network structure is relatively stable, rather than over pruning until fragmentation dominates [30]. A related application selects a quantile backbone using global efficiency diagnostics [94].

Second, *connectedness and causality* designs derive directed spillover networks from variance decompositions of multivariate volatility systems, then analyse how transmission changes once direction is retained [49]. In frequency domain designs, spillovers are estimated separately for short, medium, and long time horizons, and crises become visible as reweighting across horizons when frequency bands are treated as separate layers. Researchers measure the similarity of connectedness networks across these frequency horizons using overlap and correlation measures to diagnose heterogeneity across frequencies [38]. A complementary approach separates connectedness into distinct contemporaneous and lagged transmission layers, and uses dynamic overlap and uniqueness metrics to show that the two layers become more similar during crisis periods [40]. Overall, the evidence points to horizon-specific reconfiguration, rather than uniform amplification across time scales. A closely related set of designs defines layers by risk component instead of horizon, separating mean, volatility, and extreme risk spillover layers to test whether risk-sensitive layers carry earlier signals than the mean layer [92]. A further variant stacks realised volatility, implied volatility, and variance risk-premium layers, showing that dominant spillover channels differ between long-horizon full sample estimates and short-horizon rolling dynamics, with implied volatility more salient in the long run and variance risk premium shocks sharper in the short run [39].

Third, *institutional and infrastructure* multiplexes use tools that rank participants and identify conduits across products or clearing segments under directional stress. Modelling choices are often driven by the need to rank participants by systemic relevance under directional stress or to understand how clearing and settlement arrangements alter potential contagion pathways. These studies treat intermediaries and market infrastructure as explicit layers, and use cross-layer participation and multiplex centrality to identify participants that transmit stress across products or clearing segments, thereby providing a proxy for vulnerability to variation margin liquidity stress across derivative markets [56, 62].

Within and alongside these families, some designs derive layers from exogenous structures rather than purely statistical dependence. Examples include factor-guided layers with residual components [55], clearing markets and member roles across derivative asset classes [62], and social tie information layers among institutional investors [51]. In a more structurally specified approach, behavioural market multiplexes build layers from market microstructure, combining an informative layer governing information exchange or imitation with a trading layer that generates prices and transactions [95]. In climate-exposed commodity applications, researchers convert commodity price series into visibility graphs, treating the resulting adjacency matrices as a tensor representation of comovements, and extract time-varying network indicators from its decomposition. These indicators are then related to financial stress and climate variables using conditional Granger causality tests in a vector autoregression (VAR) [52]. Similarly, in computational finance, [96] applies multilayer partial differential equation solvers, specifically a heat-equation method, for option pricing and risk computations. This is distinct from the contagion and connectedness focus of the wider corpus, demonstrating that multilayer methods extend beyond dependence and spillover analysis.

8.4 Mechanisms, findings, and quantitative benchmarks

This subsection synthesises what changes in market network structure and stress transmission when studies keep returns, volatility, tail risk, liquidity, institutions, and infrastructure as distinct layers rather than collapsing them into an overlay. The synthesis focuses on three shifts: informationally distinct layers, crisis-driven shifts from short to longer horizons, and cross-layer conduits formed by concentrated institutions and infrastructures. These shifts connect directly to monitoring choices because each changes both who appears systemically central and how quickly stress propagates. Throughout, a node's transmission role refers to whether it is a net transmitter or net receiver of shocks within a directed spillover layer. Separately, interlayer bridging refers to cross-layer participation that enables transmission between layers. The quantitative results are heterogeneous, but a small set of recurring magnitudes anchors the gains from keeping layers separate.

Layer non-redundancy and crisis sensitivity. Dependence layers often encode different link sets, so collapsing them into an overlay can discard structure and distort inferred communities, even before any stress scenario is imposed. For example, in a dependence multiplex with distinct Pearson (linear), Kendall (rank-based nonlinear), partial, and tail-dependence correlation layers, up to 70% of edges in a given layer can be unique to that layer, and average overlap across layers is far from complete redundancy [27]. A three-layer construction comprising idiosyncratic return, realised volatility, and trade volume reports very low all-layer overlap via the Jaccard similarity coefficient of 7.95%, indicating that less than 8% of edges overlap in the multiplex [28]. When the three layers are stacked as a multiplex, modularity falls from about 0.90 in single layers to about 0.56 in the multiplex. Further, average shortest path length falls significantly from a high of about 19.7 in the idiosyncratic return layer to about 4.2, and assortativity shifts towards neutrality at about -0.07 [28]. A similar pattern appears in Chinese equities, where a two-layer spillover network for 227 stocks treats investor sentiment and returns as distinct layers, estimated using variance-decomposition connectedness and filtered using global efficiency [97]. The study shows that system-level connectedness is weaker on the sentiment layer, but it reacts sharply in crisis episodes, and the dependence between the two layers' connectedness is quantile-specific [97]. Collectively, these statistics support layer non-redundancy and demonstrate that aggregation can materially alter inferred community structure. Related evidence from Chinese financial guarantee markets points in the same direction, where a low Jaccard similarity measured across a guarantee multiplex network implies that a single-layer network is not quite representative of the multiplex, and central firms can differ by guarantee-type layer [98]. Tensor-based multiplex clustering tracks crisis episodes and can reveal structure that overlay aggregation suppresses [61], which supports the claim that aggregation flattens market stress signals. This matters for supervision because signals that appear weak in an overlay can be strong once the relevant layer is isolated. In knowledge-guided designs, separating risk factor layers from a residual layer can also reveal anticipatory shifts in multiplex diagnostics around crash episodes [55].

Crisis shifts spillovers from short to long horizons. In crisis windows, connectedness and spillovers often shift away from short horizons and towards medium and long horizons, rather than rising uniformly across time scales. This matters because it distinguishes fast repricing shocks from persistent stress, and it changes both the set of key transmitters and the interventions that are likely to be effective.

Frequency-domain multilayer connectedness networks are employed in [38] to show that crisis episodes shift spillovers away from short-term horizons and towards medium and long-term horizons: around the GFC and COVID-19, short-term average connectedness strength (ACS) falls, while medium and long-term connectedness rises, with the long-term increase especially pronounced around the Lehman Brothers' collapse. At the same time, horizon layers diverge, with similarity across frequency bands declining across multiple measures (including lower overlap and lower rank correlation), aligning with horizon-specific reconfiguration rather than uniform amplification [38]. [92] report that spillovers peak first on the extreme-risk layer, then on the volatility layer, then on the mean layer, and they find substantially higher cross-market overlap for a western subset of markets (WEST 3) than for an ASEAN subset (ASEAN 4). A complementary modelling result offers a mechanism consistent with these stress dynamics. A two-layer information and trading model provides a behavioural mechanism in line with volatility persistence, reproducing volatility clustering via informative contagion and imitation on the informative layer coupled to trading dynamics [95]. Operationally, this shifts the problem from tracking a single connectedness level to tracking which layer, and which horizon when frequency domain decompositions are used, carries transmission at each point in time.

Volatility layers dominate return layers in crisis transmission. During stress, volatility and implied-risk channels tend to carry more transmission weight than return channels, even when return layers retain unique structure. For example, in the oil and G20 stock market multiplex, risk transmission is mainly via the volatility spillover layer, and the return spillover layer's UER (a layer-distinctiveness measure) is much higher in rolling window networks (average 0.097) than in the static full sample network (0.010). This implies that the return layer becomes more distinctive when moving from a full sample estimate to rolling windows, because time variation reveals return-specific edges that are largely suppressed in the static construction [29].

In commodity futures, return, volatility, and extreme-risk spillover layers exhibit distinct transmission patterns, with short-run transmission more prominent on the volatility layer and long-run uniqueness stronger on the return layer [30]. In the static full sample networks, the return layer exhibits the highest UER (6.3%), the volatility layer is partly distinct (1.6% of volatility-only links), whereas the extreme-risk layer shows no unique edges. Further, the average edge overlap is 2.63, meaning a random spillover link appears in about 2.6 of the three layers [30]. Employing rolling windows, the volatility spillover layer, rather than the return layer, exhibits the highest UER of 11.6%. This suggests that, in the relatively short term, volatility spillover exhibits greater uniqueness than return spillover, though UER declines during major crisis windows as average connectedness strength rises, consistent with crisis-driven cross-layer homogenisation [30]. These findings indicate that rolling windows can increase return layer uniqueness relative to a static estimate, while increasing volatility layer uniqueness even more, so the most distinctive layer can switch between return and volatility depending on the construction [29, 30].

Spillover effects are strongest on the implied variance layer in the long term, while the most evident spillover shocks occur on the variance risk premium layer in the short term [39]. Stock–FX connectedness is asymmetric: stock markets transmit larger volatility spillovers to FX markets than the reverse. The main transmitters are concentrated in a subset of stock markets, particularly in Europe, while many FX markets act more as net receivers, except for the US dollar which remains a key transmitter [42]. The interconnected multilayer network structure also changes across crisis periods. This supports the same study's finding that the method signals instability during the Global Financial Crisis and COVID-19. At the liquidity spillover level, a two-layer design that separates linear from nonlinear spillovers shows low cross-layer overlap and highlights a small set of connector stocks, with the multilayer projection capturing crisis episodes that differ by layer [54]. These results connect to the next mechanism because volatility dominance becomes more consequential when trading is routed through a concentrated set of trading and clearing infrastructures and intermediaries.

Infrastructure concentration creates hidden vulnerabilities. Clearing networks link financial product classes with clearing participation in ways that price-based dependence cannot capture, so margin calls and liquidity demands can spread beyond a single centrally cleared market [62]. Euro area derivatives market data, reported under the European Market Infrastructure Regulation, show pronounced heterogeneity in participation of parties active in clearing markets: only a minority of CCPs and direct clearing members are active in a single asset-class layer (21%), a large share span four or more layers (41%), and a small core spans all layers (10%). However, indirect participants, who are direct clearing members' clients, are much more concentrated in one single layer (about 65% for credit institutions and 80% for other counterparties) [62]. Because clearing members participate in market segments simultaneously, connecting otherwise separate clearing markets, stress that appears confined to one segment can transmit across financial product classes through shared membership. This supports a shift in regulatory supervision from market-specific monitoring to member-centred monitoring across financial products and clearing infrastructures [62]. Related clearing models show that if obligations are settled in specific assets, illiquidity and sales to raise cash can trigger abrupt shifts in losses and feasible payments [37].

Cross-market spillovers mediated by institutions. Intermediaries can couple spillovers across asset classes. In a European multilayer network linking equity and credit volatility for Global Systemically Important Banks (G-SIBs), most spillovers remain within each market. However, cross-market spillover shares are non-trivial at around 0.21 from equity to credit and 0.18 from credit to equity [49]. These cross-market patterns are consistent with the broader evidence on global equity and foreign exchange systems (stock and FX), in which equities are persistent net emitters to FX and the mixed stock-FX system exhibits Total Connectedness Index (TCI) values in the 54%-90% range, representing the share of forecast-error variance attributable to cross-series shocks in a given time window and horizon [42]. Having established that institutions mediate cross-market transmission, the following studies examine which macro drivers act contemporaneously and which operate with a lag.

Drivers of spillovers. Macro drivers differ between contemporaneous shocks and lagged propagation, so attribution is most interpretable when timing is separated. Using a Shapley value decomposition, [40] shows that a composite Financial Stress Index explains most contemporaneous variation (about 62.65%), and an even larger share at lags (about 80.16%). Economic Policy Uncertainty contributes more at lags (about 10.89%), while the term spread (difference between long and short maturity yields) contributes more contemporaneously (about 19.79%) [40]. This separation supports monitoring that distinguishes contemporaneous shocks from lagged propagation, rather than pooling drivers into a single explanation. In practice, this helps distinguish fast repricing episodes from slower transmission that runs through funding, collateral, or balance sheet adjustment.

Institutional, information, and infrastructure conduits. Non-price ties and validated backbone structures can expose conduits that are not visible in dense dependence layers. Related evidence from payment and transaction networks points to persistent directional motifs that can stabilise conduit identification over time. In directed money flow networks, certain three-node directed patterns (triadic motifs) recur persistently and their intensity is predictable at daily horizons, suggesting stable underlying transaction structures [99].

Information sharing ties among institutional investors, built from colleague, alumni, parent-subsidiary, and common activity links, is associated with a higher subsequent crash risk at the firm level after controlling for public news and coverage, with weaker effects where governance and disclosure are stronger [51]. Quantile-based causality networks among US banks and insurers are substantially denser in crises than linear Granger causality graphs. Hybrid specifications that combine both approaches leave residual correlations close to zero, suggesting that nonlinear dependence dominates during stress episodes [47]. These findings complement the earlier horizon results, because they show that stress can appear first in tail-sensitive layers even when linear mean-based links look weak.

An additional operational contribution comes from stabilising and ranking conduit structures. Statistically validated investor backbones, built using significance tests with multiple comparison corrections, are far sparser than dense overlays and remain more stable across time windows. This stability is reflected in Spearman correlations for node degree sequences ranging from 0.65 to 0.99, indicating that the relative ordering of highly connected versus peripheral nodes changes little from one window to the next [67]. In practice, this reduces churn in the monitored set, so risk teams can focus on a persistent core rather than repeatedly reacting to noise driven reshuffling. This matters practically because stable ranks are easier to justify and act on than ranks that move mainly due to estimation noise in dense dependence layers.

Infrastructure multiplexes from diverse settings reinforce the same structural point: systemic relevance concentrates in a small set of participants that span layers [100]. In the UK OTC derivatives multiplex, derivative markets form three layers (interest rate, credit, foreign exchange) on a common institution set, and cross-market institutions are a small minority. Under extreme scenarios with small liquidity buffers, portfolio directionality makes spillovers concentrate in a handful of institutions, and Functional Multiplex PageRank provides a small improvement over Functional Multiplex Eigenvector Centrality when ranking vulnerability to variation margin shocks [56].

These findings also motivate clearing models that make infrastructure constraints explicit rather than treating them as exogenous or neutral. Clearing with asset-denominated obligations generalises Eisenberg-Noe to multiple assets, and once price impacts are included, multiple clearing equilibria can arise, with an adjustment process converging to an attained solution, which matters directly for stress design [37]. Consequently, this supports interventions that target the bridge set, for example margining, participation limits, or concentration-based add-ons, rather than treating each layer in isolation.

Similar concentration appears in venture capital co-investment networks, which show that concentrated syndication structures can amplify contagion when shocks originate in particular industries or propagate through highly connected syndication hubs, with herd behaviour further widening the contagion range [101]. Across these settings, the common mechanism is bridging: a small set of actors connects otherwise separate parts of the multiplex, so their failure or constraint can reroute stress rather than merely increasing it.

Sustainability, climate and digital assets. A subset of studies applies the same layer-specific diagnostics to sustainability, climate, and digital asset markets, testing whether newer risk categories display the same layer-specific patterns seen in traditional finance.

Green finance. Provincial green finance multiplexes show strengthening regional connectivity over time, with the dominant signal coming from interactions amongst economic, population, and social variables rather than any single factor acting alone [102]. Using 16 years of panel data for 30 Chinese provinces, the authors construct separate province-level spatial association networks, using a modified gravity model, with composite green finance and clean energy indices represented in layers. These layers are then coupled within a multilayer network to analyse their synergistic development [102]. At cross-country scale, finance-environment multiplexes suggest that short-term financial flows align more closely with environmental footprints than long-term flows, and that reverse-direction correlations are stronger than same-direction correlations, a pattern that aligns with burden shifting [103].

Climate transmission. Sectoral climate multiplexes show layer-specific responses to climate policy uncertainty. Using a quantile backbone selected by global efficiency diagnostics, [94] reports that the extreme-risk layer becomes sparse earlier than the return and volatility layers as filtering strengthens, so layers do not move synchronously. During climate uncertainty episodes, the inferred spillover structure differs across layers in sparsity and direction, which supports monitoring that separates return, volatility, and tail-sensitive channels rather than relying on a single aggregated network [94]. In parallel, visibility graph indicators, which transform time series into networks, exhibit systematic pre-crisis shifts in commodities, equities, and financial stress, offering a route to layer-aware monitoring for climate-exposed markets without depending on a single proxy [52, 53].

Crypto and digital markets. In multiplexes linking major crypto assets to China's stock market and exchange rate, returns and volatility are strongly connected while extremes show weaker connectivity. Major crypto assets tend to be net transmitters, while the China stock market and exchange rate nodes appear more as receivers, and regime changes such as bans, the pandemic, or geopolitical shocks reweight layers rather than shifting all channels uniformly [93]. Token infrastructure multiplexes are structurally centralised: removing a small set of exchange or contract hubs fragments the core. Moreover, dismantling one layer alters connectivity elsewhere, indicating direct cross-layer dependence rather than a purely within-layer effect [100]. Related non-bank network evidence points in the same direction: Chinese corporate guarantee multiplexes are scale-free and disassortative with small pairwise layer overlaps, reinforcing that aggregation can erase meaningful cross-channel distinctions [98].

Across these settings, the common finding is that layers remain non-redundant and regime-sensitive, with transmission shaped by a small set of concentrated conduits. As elsewhere in this review, the evidence confirms that distinct layers carry information that changes inferences, rankings, and timing relative to aggregated overlays.

8.5 Implications

Four operational messages recur, each linked to a concrete monitoring or stress testing choice.

The first operational priority is to preserve layers, because correlation overlays can discard layer-unique links and can distort monitoring-relevant structure, for example community separation and path length, once layers are combined into a single graph [27, 28, 61]. Where connectedness is estimated, monitor it separately for returns, volatility, and tail risk, and decompose it by horizon (short, medium, long) [38]. Further, cross-market monitoring becomes important when institutions span markets, as these institutions can transmit shocks across otherwise separate segments [49, 92].

Second, inference must be stabilised before drawing conclusions. Statistically validated backbones produce sparser and more stable signals, and for clearing this supports stress testing at the level of the member across products and across CCPs, given multilayer participation [62, 67].

Third, integrate microstructure and design choices, because multiplex structure can affect both predictability and cascade regimes. Liquidity spillover multiplexes and cross-asset spillover couplings can improve crisis identification and stabilise the set of key transmitters, receivers, and connectors for monitoring [54, 92, 95].

Fourth, incorporate institutional information layers where available. Social tie indices among institutional investors add predictive content for crash risk beyond prices alone, and member-centric oversight across CCPs can use directionally sensitive multiplex centralities to rank systemic participants [51, 56, 62].

These implications support a Map–Monitor–Test–Intervene workflow for regulators, practitioners, and researchers. This involves mapping distinct system channels, monitoring layer-specific and horizon-specific rewiring on stabilised backbones, stress-testing microstructure and infrastructure linkages explicitly, and intervening on channels and participants that remain systemically central once information and clearing layers are included.

8.6 Limitations and future directions

Limitations in market multiplex studies fall into two broad categories: construction sensitivity; and identification and data constraints. Construction sensitivity means results can shift with backbone thresholds, rolling window choices, horizon definitions, and the dependence or tail estimators used. Replication therefore requires transparent reporting of construction choices and their rationale [38, 53, 67]. Further, many designs are associative rather than causal. Unlike banking research, where frequent regulatory changes and interventions provide natural experiments for causal analysis, market-based studies face limited scope for identifying causal effects through policy changes or quasi-experiments. Many market designs rely on variance-decomposition connectedness measures, which are primarily predictive summaries of shock transmission rather than structural causal identification [39]. Even when studies use Granger-style or quantile causality, these links still require strong assumptions for causal interpretation and remain specification-sensitive [47, 54]. Finally, static multiplex analyses would benefit from applying dynamic measures and modelling how financial stress might propagate through the framework [28, 62].

Despite these constraints, the evidence suggests that layer-preserving, stabilised designs are the most promising route for practical monitoring and stress design in market multiplexes.

9 Global Systemic Risks

9.1 Scope and corpus

At the scale of financial systems, multilayer networks improve the measurement and management of systemic risk by preserving distinct transmission channels. The forty-three studies reviewed here show that financial stability depends on the interactions across distinct transmission channels, including interbank credit and funding, overlapping portfolios and price-mediated feedbacks, cross-border positions, and spillovers across statistical moments. Each channel defines its own nodes and edges and evolves on different time scales, so a single aggregated graph fails to capture essential structural dependencies. Systemic risk emerges when distress propagates through several channels simultaneously, with outcomes shaped by layer coupling and time horizon in ways that institution-level analysis alone cannot capture. This motivates the coupled layer architectures described below.

9.2 Data and layer architecture

The literature offers replicable network designs spanning three levels of analysis: institution-level balance-sheet and market layers, bank–firm multiplexes, and cross-border multiplexes.

At the institution level, studies represent direct exposures between institutions as one layer and indirect exposures induced by overlapping portfolios as a second layer constructed from institutions' holdings. Together, these coupled layers capture two propagation mechanisms: counterparty default through direct links and price-mediated contagion through common holdings [31, 33]. This framework is illustrated in Figure 10. Complementing these balance-sheet constructions, information spillover layers capture directed transmission across statistical moments (means, volatility, and extreme risk), allowing researchers to distinguish which moments facilitate shock transmission across institutions [71]. Frequency-domain multiplexes extend these information-spillover designs by separating connectedness into short, medium, and long horizons, allowing frequency-specific dynamics to be analysed within the same node set [43].

Global bank–firm multiplexes link the financial sector to the real economy, to assess systemic risk. Feedback-based designs treat banks and firms as distinct node sets. They combine an interbank exposure layer with cross-layer bank–firm lending links, and, where available, an additional firm liability layer or a cross-holdings layer for financial instruments that closes the feedback loop. Two-layer constructions can separate credit exposures by maturity, while tri-layer systems capture feedbacks between firm cash flows, bank funding conditions, and commonly held asset prices [34, 60, 75, 104]. A related approach reconstructs a credit multiplex by coupling an interbank credit layer to a bank–firm credit layer, enabling DebtRank-based contagion simulation across both channels [105]. In the Brazilian application, omitting bank–firm feedback understates losses and can reorder the most systemic firms or sectors [104]. A related stress testing family couples bank–firm credit, bank portfolio holdings, and interbank lending within one multilayer architecture, so that shocks from firms, assets, or banks propagate across channels rather than being analysed in isolation [60, 106].

Cross-border multiplexes operate at the country level, with layers representing equity positions, debt holdings, and banking exposures across jurisdictions [36, 107]. Some designs use banking tensors that distinguish borrowing-side risk from lending-side risk for the same country pair [69], whilst others construct sovereign risk information networks that track how stress signals propagate across national boundaries [108, 109].

Across all three levels, layers are kept separate but explicitly coupled, enabling the following methods to attribute amplification to specific cross-channel feedbacks rather than to an undifferentiated aggregate [31, 36, 43, 110–112].

9.3 Methods, in brief

Methods can be grouped into six categories based on their operational focus. While differing in outputs, they share the design principle of explicitly preserving distinct layers and horizons.

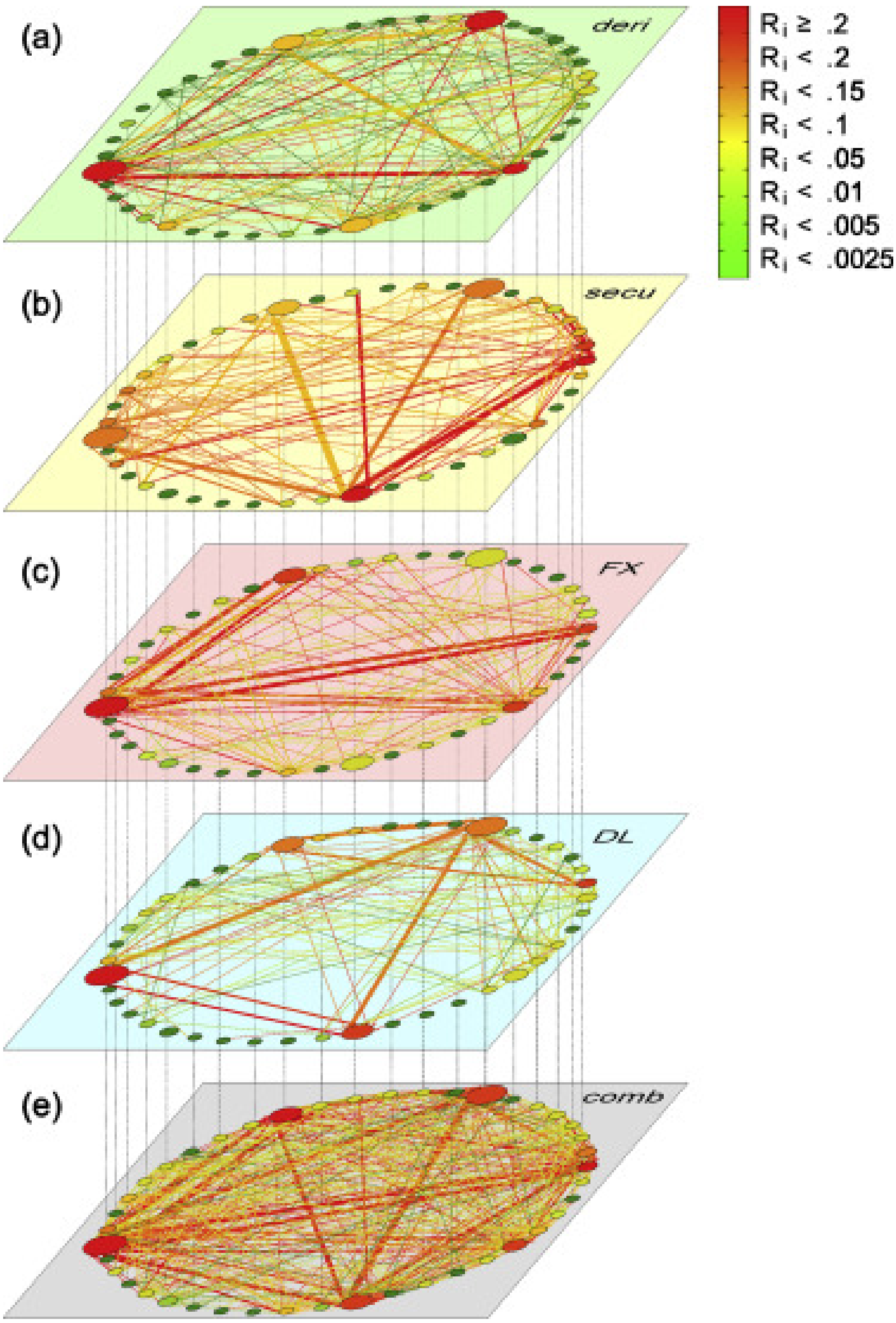

Fig. 10: Banking multilayer network of Mexico on 30 September 2013. (a) Network of exposures from derivatives, (b) security cross-holdings, (c) foreign exchange exposures, (d) deposits and loans, and (e) combined banking network. Nodes (banks) are coloured according to their systemic impact in the respective layer: from systemically important banks (red) to systemically safe (green). Node size represents banks' total assets. Link width is the exposure size between banks, link colour is taken from the counterparty. (Figure reprinted from [31], with permission from Elsevier.)

Foundations and general machinery

This category provides tools to derive stability conditions and compact descriptors for coupled systems, so that surveillance can distinguish stable from unstable regimes without relying on a single scenario.

Spectral diagnostics derived from eigenvalue-based shock transmission matrices provides stability measures for coupled systems [32]. Frequency-domain connectedness builds horizon-specific layers using a time-varying parameter vector autoregression (TVP-VAR) approach, sparsifying networks using thresholding techniques [43]. For compact surveillance, three descriptive measures summarise multiplex structure over time: average overlap degree (AOD), average connectedness strength (ACS), and network correlation coefficient (NCC) [43, 59]. These descriptors are useful precisely because they can move even when aggregate density does not, so they help avoid false reassurance from an apparently stable overlay. Complementing these diagnostics, network econometric designs estimate the probability of link formation directly using exponential random graph models (ERGMs), and in an international multiplex of financial claims higher financial concentration is associated with an average 5.60% lower probability of forming new edges [111].

Identification of systemic institutions

This category turns multiplex positions into a prioritisation list for supervision, either as a single composite score, a conditional loss contribution, or a time evolving rank. The literature offers three methodological routes for translating multiplex network position into measures of systemic importance: composite scoring, conditional loss models, and temporal multiplexes. Table 3 summarises the layer construction, importance measure, and output for each.

Using these methods, composite scoring outputs a single ranked list [65], conditional loss models output time-varying ΔCoVaR and estimate its association with multiplex network indicators [66], and temporal multiplexes produce time-evolving importance scores by computing centrality on a coupled block matrix that links networks across regimes and horizons, with tunable coupling strength [70].

These designs thus translate multiplex position into supervisory outputs that can diverge materially from single-layer rankings [65, 66, 70]. The tools directly support the Monitor step in an operational workflow by allowing practitioners to prioritise firms and institutions by channel and over time. They also clarify the optimisation objective, whether it is ranking agreement, conditional loss magnitude, or temporal persistence.

Contagion and cascades

This category models non-linear amplification when default, liquidity stress, and price-mediated channels interact, so that ranking and stability can be stress-tested under coupled dynamics rather than inferred from static topology. Propagation models join price-mediated overlap, interbank default, and bank–firm feedback engines [33, 34, 104], while cyclic structures capture amplification through looped interlayer paths [35].

Eigenvalue-based shock transmission matrices formalise how interacting contagion channels jointly transmit distress. In scenario-free stability screening, these channels are collapsed into a transmission matrix whose largest eigenvalue governs system

Table 3: Three methodological routes for identifying systemically important institutions

Method route	**Layer construction**	**Systemic importance measure**	**Output**
Composite scoring [65]	PMFG correlation-filtered layers and volatility spillover layers via variance decomposition, each built for price volatility and investor sentiment	TOPSIS ranking combining layer-level centralities, spillover indicators, and market value	Single ranked list with per-institution scores
Conditional loss [66]	Dependence layers: linear (Pearson), rank-based (Kendall), and tail, with tail dependence estimated via a time-varying Student t-copula with DCC dynamics; PMFG backbone	Time-varying Student t-copula ΔCoVaR, the change in CoVaR between a benchmark state and an institution distress state	Time-varying ΔCoVaR estimates and rankings, with multiplex network indicators mapped to ΔCoVaR
Temporal multiplex [70]	Quantile-coherency layers capturing co-movement across market regimes (bear, stable, bull) and horizons	Eigenvector centrality on supra-adjacency evolution matrix	Time-evolving importance scores with tunable cross-slice coupling

Note: PMFG is a planar sparse backbone used to retain the strongest links while reducing noise in dense dependence estimates. TOPSIS is Technique for Order Preference by Similarity to Ideal Solution. DCC is Dynamic Conditional Correlation, a time-varying correlation model used to model time variation in dependence estimates.

stability, with values below one implying shock damping and values above one implying amplification and therefore instability [32]. A key implication is that stability can deteriorate through cross-channel feedbacks even when each layer, viewed alone, appears benign [113].

Cross-border and macro-financial spillovers

For banking and sovereign exposures, country-level multilayer designs separate borrowers from lenders [69], and distinguish transmitters from receivers of stress, using multiplex position to retain directionality and reveal contagion pathways [36, 108, 109]. Banking tensors represent each bilateral relationship from both perspectives, so borrower-side and lender-side exposure channels can be analysed explicitly [69]. Complementary information spillover multiplexes then use directed links in return, volatility, and extreme risk layers, with multiplex position measures such as out strength and cross-layer participation, to track how sovereign risk transmission shifts across layers and across stress episodes [109].

For energy and geopolitical transmission, connectedness frameworks use wavelet-based diagnostics and Dynamic Equicorrelation GARCH (generalised autoregressive conditional heteroskedasticity) to separate contemporaneous from lagged spillovers across assets. These frameworks also compare spillover topology across mean, volatility, and extreme risk layers in multilayer information networks linking oil shocks to banking sectors [45, 46]. For extreme-risk spillovers, Conditional Autoregressive Value at Risk (CAViaR) networks combined with non-linear causality tests are used to identify tail-risk transmission paths [41].

Regional empirical evidence

This category examines within-jurisdiction validation designs, using China as a recurring empirical setting. Typical designs keep a set of institutions fixed and vary layers by transmission channels or time horizons. They include balance sheet exposure multiplexes that compare systemic risk contribution across coupled layers [74], directed information spillover multiplexes that separate mean, volatility, and extreme risk (tail) [73], idiosyncratic volatility connectedness networks that distinguish contemporaneous from lagged spillovers [114], and frequency domain connectedness multiplexes that split connectedness by horizon [43, 59]. There are two-pillar tail-risk monitoring frameworks that combine a tail-risk dependence network with a tail-risk vector autoregression [72], and stress loop simulations that propagate firm distress through bank, firm, and asset layers with PageRank-based systemic scoring [60].

Policy, regulation, and risk mitigation

This category summarises methodological designs that map multilayer diagnostics into intervention frameworks, primarily portfolio rewiring, resolution simulation, and coupled stress testing. The emphasis is on translating multilayer risk maps into supervisor-facing mitigation tools and stress testing workflows [112].

Network-aware portfolio optimisation is formulated as a rewiring of common exposures across institutions under risk-return constraints [115]. Resolution frameworks evaluate bail-in mechanisms [116] and loss-absorbing capacity requirements, examining how write-downs propagate through multiplex structures [117]. Stress designs join solvency and credit losses, market liquidity and settlement frictions, and fire-sale driven valuation spillovers [106, 118], with some extending the perimeter to include links to Financial Market Infrastructures (FMIs) [118]. Operational evaluation is implemented via simulation-based tools, combining multilayer agent-based models for intervention testing and stress mapping workflows that simulate interventions under cross-layer feedbacks [119, 120], and epidemic-style multiplex stress mapping for forecasting crisis propagation [121], implemented by fitting a susceptible–infected–recovered process on a four-layer multiplex with estimated transmission and recovery parameters.

9.4 Mechanisms and key findings

A central empirical finding emerges across datasets and designs: coupling between layers raises losses and lowers stability thresholds. Omitting overlap understates losses by approximately half in supervisory data. Focused single-exposure views can understate systemic risk by as much as 90%, and critical leverage is overstated by 45 to 300% when ignoring interactions between contagion channels [31–33].

In Brazilian supervisory and accounting data, adding explicit two-way bank–firm feedback, where firm distress weakens banks and banks respond by tightening credit, generates additional propagation rounds and can materially increase measured systemic losses relative to a no feedback baseline [104]. In the bank–firm–asset framework, bank failure triggers bankruptcy liquidation, which forces asset sales and loan recovery, depresses shared asset values, reduces firms' loan acquisition, and transmits losses back to other banks via overlapping portfolios and interbank lending exposures [106]. A complementary variant replaces the explicit asset layer with exogenous macroeconomic scenarios, and shows how leverage, loan maturity, and capital adequacy mediate the probability and timing of bank and firm defaults in the coupled bank–firm and interbank system [122]. Systemic rankings can reorder across layers [75, 105], and can also rotate with horizon and regime, so systems that appear robust in one view can contain latent hubs in others [70]. Amplification can be superadditive because feedback loops can run through cycles that span layers. One study shows that a two-layer network produces more systemic distress than the sum of the layers analysed in isolation [35]. For cyclic structures involving inter-layer links, the multilayer systemic distress risk is 0.0750, while the two single-layer values sum to 0.0225, hence a risk amplification of 0.0525, showing that inter-layer feedback can generate losses that are not captured by simply summing the two single-layer results. The study also reports that cyclic structures generate larger amplification effects than feedback mechanisms alone or inter-layer links alone, suggesting that feedback loops allowing distress to compound are a key factor driving risk amplification in multilayer settings.

9.4.1 Cross-border sovereign risk, commodities, and policy shocks

This subsection synthesises cross-border and macro-financial evidence where shocks propagate through multiple channels, and where multilayer designs retain direction, exposure type, and horizon so borrower versus lender vulnerability and shock timing can be distinguished.

Classification and two-sided banking risk

Network-modified spreads, which are borrowing cost spreads adjusted for contagion through the international banking network, are approximately three to four times larger than single-country estimates for peripheral borrowers, and they also rise materially for core lender countries. On the borrowing side, expected losses are dominated by very large debtors such as the United States, consistent with exposure size playing a larger role than unusually high spreads; on the lending side, the United Kingdom, France, and Germany dominate, followed by the United States and Japan [69]. The key implication is that system-wide vulnerability is shaped as much by who is large and connected as by who looks risky in isolation, so surveillance and stress tests that neglect network linkages can misidentify both the main sources of risk and the countries most exposed to contagion. Moving from pricing to classification, a multiplex over banking, debt, and equity positions identifies about twice as many systemic countries as any single layer at a one third threshold and avoids false positives and false negatives created by aggregation, with equity gaining influence over 2009 to 2019 [36]. Supporting this, sovereign risk information networks show role shifts in stress, with multiplex out strength and participation revealing under-recognised spillovers [109]. Taken together, these results support a single operational point: multilayer structure helps disentangle who is exposed, through which channel, and how systemic labels change once borrower and lender roles are separated.

Energy and geopolitics

Here the primary mechanism is that events can shift spillovers across assets and horizons. A dynamic Equicorrelation Generalised Autoregressive Conditional Heteroskedasticity (GARCH) connectedness framework separates contemporaneous co-movements from lagged spillovers. Using this approach, average total connectedness between geopolitical risks and energy markets is moderate at about 29%, with around 77% attributed to contemporaneous spillovers and 23% to lagged spillovers, with overall connectedness rising around major episodes [45]. Directionality also depends on the component: geothermal, solar, gasoline, West Texas Intermediate (WTI), and heating oil are net transmitters in the total and lagged measures, however, in the contemporaneous measure, gasoline and geothermal become net receivers [45].

A related multilayer design links oil market shocks to banking exposure by separating spillovers into mean, volatility, and extreme risk layers. Oil supply shocks show strong connectedness with banking sectors in the volatility and extreme risk layers but weaker connectedness in the mean layer, oil demand shocks show strong connectedness in all three layers, and oil market risk shocks show no connection with banking sectors in the extreme risk layer but strong connectedness in the mean and volatility layers [46]. This matters because the inferred oil sector to bank sector transmission route changes with both shock type and risk channel, so monitoring based on a single channel can miss where exposures concentrate under stress.

Broadening the scope beyond the oil sector, extreme risk multiplexes for the G7 and BRICS (Brazil, Russia, India, China, South Africa) find that stock markets are net emitters, with bonds and credit as net receivers, and with density and clustering rising in crises [41]. Energy and geopolitical shocks thus alter both direction and horizon of transmission, so single-horizon summaries can misstate the dominant transmitters.

Fiscal and institutional channels

These papers treat fiscal, accounting, and unconventional monetary policy as structural changes that rewire dependence rather than simply scaling volatility. Fiscal stress transmits through state, bank, firm loops, but high capital at key creditor banks limits second-round losses in idiosyncratic state defaults in Brazil [123]. At global scale, accounting convergence through International Financial Reporting Standards (IFRS) reduces bilateral dependence and lowers pass-through by about sixteen to twenty three percent through diversification and comparability [124]. In the euro area multilayer macro network of sectoral balance sheet exposures, the period following the start of an asset purchase programme, known as Quantitative Easing (QE), is associated with faster growth in intra-financial linkages than in finance to real-economy linkages, with aggregate intra-financial interactions rising by 18.19% versus 8.09%, largely driven by loans and deposits (19.75% intra-financial growth versus 4.22% to the real economy) [125]. The study interprets this pattern as consistent with balance sheet expansion strengthening within finance connectivity more than finance to real activity, while stressing that the evidence is temporal and does not establish a causal effect [125].

Across these interventions, the shared message is that policy and institutional settings can change the network pathways that matter, so monitoring needs to be layer aware rather than purely market wide.

Coupling and stability thresholds

The final strand makes the stability logic explicit: cross-market coupling can shift a system from stable to unstable even when each channel alone appears contained. In a two-layer Susceptible Infected Susceptible (SIS) contagion model linking commodity and financial markets, the basic reproduction number, R_0, exceeds one under coupled dynamics, which implies expanding cascades [113]. In a dynamically evolving bank–firm credit and interbank lending model driven by exogenous macroeconomic scenarios, firm distress feeds back into bank losses and credit supply, with interbank funding providing an additional propagation route when capital constraints bind [122]. This complements the earlier evidence by linking multilayer structure directly to stability conditions, not just to classification or spillover direction.

9.4.2 China

Seven studies apply the within-jurisdiction multilayer designs summarised above under Regional empirical evidence, allowing horizon and channel dependence to be evaluated within a single setting [43, 59, 60, 72–74, 114].

In a two-layer financial institution network built from interbank lending and cross-shareholding ties, multilayer systemic risk contribution (SRC) exceeds the sum of single-layer SRC values. In the same setting, linkage diversity is more strongly associated with SRC than connectivity alone, and system-wide loss co-moves with cross-layer dissimilarity [74]. This points to cross-layer composition as a stronger risk signal than any single connectivity statistic.

A complementary strand uses multilayer representations to characterise spillovers and volatility regimes. Multilayer information spillover networks report that different spillover layers have distinct network structures and distinct evolution over time. They also propose early warning indicators using multilayer diagnostics, including uniqueness edge ratios (UER) and edge overlap, which help track how institutions contribute differently by layer as the system evolves [73]. These indicators remain informative when aggregated overlays appear stable: UER captures layer-specific spillover links, while average edge overlap captures shared links, and both metrics vary between stable and stress periods. In idiosyncratic volatility connectedness networks, contemporaneous spillover connections strengthen in stress periods, while the long-run structure remains stronger on average [114]. In the same setting, overlap between the contemporaneous and lagged layers is low in stable periods and increases in downturns [114]. Further, reported drivers vary by institution type. Larger institutions are more likely to be connected by spillover links, yielding higher node degrees. However, leverage and profitability show the opposite pattern: higher leverage is associated with lower connectedness, and higher profitability (proxied by return on equity) is also associated with a lower likelihood of spillover links in both the contemporaneous and lagged layers [114]. This reinforces the need to separate size, balance sheet characteristics, and network position, because the sign of association can flip across covariates and across layers.

Policy-oriented diagnostics formalise these signals into operational indices. A two-pillar framework combines a Least Absolute Shrinkage and Selection Operator (LASSO) ΔCoVaR network, where Value at Risk (VaR) is a tail loss quantile and CoVaR is the system VaR conditional on an institution being under stress, with a TVP-SV-VAR model (time-varying parameter vector autoregressive model with stochastic volatility). The framework also defines three indicators: VTN (a time-varying variance index combining tail-risk spillovers and return volatility), NVE (a network volatility effect that rises before spillover effects during downturns, providing early warning), and NCI (a contagion intensity measure). The framework is used to evaluate how monetary and macroprudential policies jointly affect risk transmission, with evidence that coordinated policy interventions enhance financial stability more effectively than either tool alone [72]. The operational contribution is a small set of interpretable series suited to routine monitoring, rather than reliance on a single static network snapshot.

In the same Chinese context, one study constructs a three-layer banking network for 2021, comprising interbank lending, bank–firm credit, and bank–asset portfolio holdings [60]. The network is highly concentrated: in the bank–firm credit layer, ten large commercial banks account for 55% of credit linkages and 69% of credit transactions. Bond investments and trading financial assets are prominent in the portfolio layer, and manufacturing has the highest cumulative exposure (total PageRank) while wholesale and retail trade and real estate have high average influence (average PageRank) [60]. The systemic ranking produced by the PageRank-based measure aligns with stress test outcomes, demonstrated under stress test settings that restrict firm loan access and include asset price impacts from asset liquidation, where failure of one or two core banks can generate system-wide bank defaults [60]. This aligns with the broader concentration mechanism: a small core of large banks can dominate propagation across layers even when peripheral layers appear sparse.

Frequency domain connectedness designs add a horizon-specific view of systemic risks [43]. During the 2015 crash and the pandemic, long-term connectedness rises relative to tranquil periods, and the composition of systemically important institutions shifts with horizon, with influence moving beyond the banking core in the medium and long-term layers [59]. Furthermore, market structure and roles are regime and horizon dependent. For example, average overlap degree (AOD) approaches one at stress onsets, meaning that the edge structure of connectedness networks is heterogeneous and each layer contains unique information that is not well captured by other layers [59].

The China evidence thus supports horizon-specific monitoring over static rankings, given that sector and institution leadership rotates across layers and market regimes [59, 73, 114]. Moreover, because concentration and cross-layer bridges can still dominate stress outcomes, monitoring benefits from separating channels and horizons, and tracking cross-layer link concentration [60].

9.4.3 Quantitative Summary

The following magnitudes reappear across studies and are useful as benchmarks.

These magnitudes are sample-specific and should be interpreted as indicative benchmarks rather than universal constants.

Table 4: Key magnitudes and sources. All magnitudes are sample-specific.

Effect	Magnitude	Source
Systemic risk understatement when overlap layers omitted	up to 50%	[33]
Large-bank systemic risk underestimation when bank–firm feedback is omitted	Average 267%, maximum 500% underestimation versus interbank-only baseline	[34]
Critical leverage overestimated by single channel benchmarks	45 to 300%	[32]
Expected systemic losses post- vs. pre-global financial crisis	up to 4×	[31]
Underestimate of total systemic risk when focused on a single exposure layer	up to 90%	[31]
Risk amplification: extra systemic distress when layers are coupled rather than analysed separately	0.05250	[35]

9.5 Implications: Policy, regulation, and risk mitigation

Four intervention levers recur across the studies.

Portfolio rewiring can dominate uniform capital increases. Systemic-risk-efficient allocations over European sovereign portfolios reduce expected cascade losses, a proxy for systemic risk, by more than a factor of two relative to the European Banking Authority 2016 baseline and avoid the very large equity additions implied by leverage-only or equity-only interventions under severe fire-sale stress. Optimised allocations break commonality whilst preserving risk-return constraints [115].

Resolution design in networks. Creditor bail-ins with moderate write-downs reduce system loss relative to insolvency and often relative to bail-outs for idiosyncratic mid-sized failures, but distributional effects can make a meaningful minority of creditors worse off for extreme shocks [116]. Cross-holdings of loss-absorbing capacity instruments, including Total Loss Absorbing Capacity (TLAC) and the Minimum Requirement for own funds and Eligible Liabilities (MREL), are generally small, so direct contagion from bail-ins is limited. However, post-resolution networks become denser and more centralised around the resolved bank, which argues for caps on cross-holdings and monitoring second-round effects [117].

Stress testing with coupled channels and infrastructures. Supervisory exercises need solvency, funding, and price-mediated feedbacks in a single workflow [112]. The operational distinction is between fast repricing spillovers and slower balance sheet or funding transmission, which often calls for different monitoring frequencies [45]. Country-level stress tests should also be network-aware, because indirect cross-border linkages can shift attention away from who looks risky in isolation towards who is large and central in international banking links, and therefore towards where contagion-adjusted exposures and losses may concentrate [69]. Further, stress testing should include non-banks and FMIs, for example payment and securities settlement systems, since connecting banks to these infrastructures can alter resilience by changing modularity [118]. Coupled macro stress tests show bank capital, firm–bank connectivity, and bank–asset density interact to shape default probability and propagation cycles

[106]. Regulator-facing multilayer agent and system-testing blueprints use simulation-based workflows to evaluate proposed interventions under cross-layer feedbacks before operational rollout [119, 120]. Finally, scenario-free stability analysis supports screening by separating stable regimes from regimes that can amplify even modest initial shocks [32].

Institutional and market settings that change structure. IFRS adoption reduces bilateral dependence and pass-through in cross-border exposures [124]. QE is associated with a larger rise in within-finance linkages than in finance to real-economy linkages, with within-finance interactions rising by 18.19% versus 8.09% for real-economy linkages; the study does not claim a causal effect of QE on increasing financialisation [125]. Concentration reduces international financial tie formation probabilities, with implications for regulatory policy that go beyond standard concentration indices [111]. Policy institutions discuss multilayer approaches, but many applications remain at the prototype or research stage rather than embedded in routine supervisory workflows [126, 127].

9.6 Limitations and further research

Data and external validity. Several headline magnitudes are estimated from supervisory datasets or reconstructed portfolio holdings, so reported effect sizes are sample-specific and should be recalibrated before being used outside the original study setting [31, 33, 60, 106]. Even when networks are estimated from market data, external validity can still be constrained by the institutional setting and the sample window, as illustrated in the Eurozone application [108].

Estimator and parameter sensitivity. Connectedness estimates vary with window length, step choice, and backbone filtering [43, 108]. Rankings and their timing are also sensitive to tail-dependence specification and vector autoregression choices [72]. In simulation-based stress propagation, price impact and leverage targets shape third-round effects, while spectral stability bounds depend on channel strength parameters, linearisation, and pass-through strengths [32, 33, 66, 70]. Composite identification introduces an additional sensitivity, since TOPSIS-style weighting and score aggregation can reorder systemic rankings even when layer construction is held fixed [65]. These parameters most directly determine whether multiplex outputs diverge from single-layer baselines, so they should be reported as primary design choices and varied in robustness checks [32, 43, 65, 66].

Identification versus description. Much of the literature is descriptive or simulation-based. Causal designs are strongest where policy shocks create quasi-experiments, such as IFRS adoption and QE windows [124]. Some feedback-based contagion models are single-period and target very short-run consequences, with iterations representing convergence of the propagation process rather than economic time [104]. Even where models are formally estimated, validation is often retrospective, and benchmark performance during crisis episodes can remain too weak for practical early warning, so the framework is positioned as proof of concept rather than a deployable early warning system [121].

Scope gaps. Non-bank intermediation beyond large insurers and securities firms is only partly covered; links to FMIs are documented but not yet standard in stress pipelines; macro multiplexes that couple trade and foreign direct investment to financial layers are not routinely integrated [110, 118].

Ranking ambiguity and uncertainty. Different centralities and composite schemes can reorder institutions, and weight choices embed norms; uncertainty for ranks and diagnostics is rarely reported as intervals [65, 66, 70]. This uncertainty is compounded when monitoring mixes fast repricing spillovers with slower balance-sheet and funding transmission, since the implied sampling frequency and windowing choices differ by channel [43, 66].

Future research agenda. Progress on multilayer systemic risk work depends on four practical strands. First, replication needs clear standards for layer definitions, sparsification rules, window and frequency band selection, price impact and recovery specifications, leverage targets, and code disclosure so that results can be re-estimated and challenged across jurisdictions. Second, empirical robustness should rely on multi-window and multi-filter ensembles with explicit out-of-sample tests, and on quasi-experiments that exploit changes in accounting standards, margining regimes, or portfolio guidance as natural experiments for identifying pass-through rather than simple association. Third, macro-to-micro workflows should integrate motif-targeted supervision, horizon-aware indicators (such as NVE and NCI), and links to central counterparties and payment systems within a unified multiplex stress-testing architecture, rather than treating these as separate diagnostics. Fourth, supervisors should conduct pilot exercises that actively rewire portfolios to reduce common exposures across major institutions and then measure how such rewiring changes multilayer amplification relative to business-as-usual allocations.

9.7 Section summary

Across the forty-three studies, multilayer representations reveal materially higher risk than single-layer approximations, because isolating channels yields over-optimistic stability margins once cross-channel interactions are included [32]. Coupling also changes supervisory priorities by shifting losses and rotating systemic rankings across layers, horizons, and regimes, including reordering once bank–firm feedback is modelled explicitly [31, 33, 34, 43, 59, 71, 104]. Table 4 summarises the main order-of-magnitude benchmarks.

10 Conclusions and Outlook

10.1 Summary of Contributions: Magnitude and Utility of Multilayer Frameworks

Across the 112 studies, multilayer networks recover transmission structures and feedback pathways that single-layer baselines suppress. The central message is that aggregation of distinct layers into an overlay can materially understate systemic losses, while single channel analyses can overstate financial stability by omitting cross-channel feedbacks.

Three benchmarks illustrate the magnitude of underestimation induced by single-layer baselines.

- Omitting overlapping-portfolio exposures and focusing only on direct interbank links can understate systemic risk by up to 50% [33].
- Scenario-free spectral conditions, a stability test not tied to a chosen stress scenario, imply that single-channel benchmarks can overestimate the critical leverage threshold by 45% to 300% when interactions between contagion channels are included [32] (see Section 9 and Table 4).
- In calibrated bank–firm feedback settings, including interlayer feedbacks raises DebtRank-measured systemic risk for large banks by an average 267% and up to 500% relative to an otherwise no-feedback specification [34].

These figures provide orientation, and the full synthesis and tables provide the underlying modelling context and comparators.

Beyond these benchmarks, results consistently show higher estimated systemic losses once key transmission channels are represented as separate but coupled layers rather than as collapsed overlays (see Sections 7.4 and 9.7). This is not simply a change in magnitude; it changes attribution as well. Institutions that appear peripheral in a single-layer can become systemically important once interlayer links are included, and the ordering of institutions by systemic importance can change when multiple channels are included in a single coupled multilayer model rather than analysed one at a time (see Sections 7.5 and 9.7). Roles in stress propagation, for example net transmitters, net receivers, and interlayer bridges, can also vary across market regimes and across short and long horizons (see Section 8.4, and Section 9.4.2 for regime and horizon rotation in banking contexts). In stress periods, layers often become less distinct because overlap across layers rises and spillovers reweight from short towards longer horizons (see Section 8.4). These shifts change which institutions and channels warrant attention at any given time, even when aggregate risk measures move only slightly [38, 71].

Across the corpus, where studies explicitly compare multilayer outcomes against layer collapsed overlays, the modelling simplification has a consistent direction of error: collapsing layers into an overlay typically underestimates losses and overstates stability margins [31, 32] (see Sections 9.4.3 and 9.7, and Table 4). The size of understatement is material rather than marginal, ranging from roughly 50% to 90% depending on the omitted channel and the calibration setting [31, 33] (see Section 9.4.3 and Table 4). This directional error motivates layer-preserving mapping and joint stress testing, meaning stress tests that model multiple coupled channels simultaneously, when the aim is to calibrate liquidity and reserve buffers, set internal risk limits, or rank systemic importance.

Three synthesis results matter for researchers, risk managers, and supervisors (see Section 3.2; Sections 7.4–7.5, 8.4, and 9.7). First, layers are rarely interchangeable, each layer preserves distinct structure but aggregation obscures it. Second, interlayer coupling is typically the dominant source of amplification, tightening stability margins relative to single-layer models. Third, systemic importance is state dependent, with shock transmission concentrating in a small set of interlayer bridges, including market infrastructures in stress.

10.2 Operational message

We recommend retaining distinct layer identities where data allow, tracking how edges and transmission roles change across layers and horizons, testing interventions within a multilayer stress-testing framework rather than treating channels in isolation, and comparing multilayer outcomes against single-layer baselines to quantify amplification. The Map–Monitor–Test–Intervene workflow below summarises a practical implementation consistent with the evidence across domains. The techniques and methods synthesised for this review provide a practical starting point for implementation of multilayer network analysis in finance and in other networked risk settings where distinct transmission mechanisms interact.

Practical workflow (Map–Monitor–Test–Intervene). Building on the evidence synthesised across application domains (Sections 4 to 9), this review distils the results into a four-step operational workflow for researchers, practitioners, risk managers, and financial stability supervisors. This workflow draws particularly on data architectures from bank–firm and interbank networks (Sections 4 and 7), connectedness and centrality methods from financial markets and macro-systemic risk studies (Sections 8 and 9), and policy levers identified in contagion and mitigation frameworks (Section 9).

1. **Map** exposure-level multiplexes using a shared schema for instruments, maturities, and horizons, and keeping layers separate so that credit, funding, and price-mediated channels can be distinguished in later analysis. (See layer constructions detailed throughout the review.)
2. **Monitor** how layer distinctiveness and connectedness evolve in rolling windows, using measures such as ACS, AOD, and NCC, and track how multiplex centralities change across institutions and sectors as market states change [43, 65, 70]. (See Sections 8 and 9.)
3. **Test** solvency, funding, and price-mediated channels jointly under stress scenarios with adverse shocks, treating cross-border, supply chain, real economy, and information layers as additional coupled layers where data allow, including non-banks and financial market infrastructures [118]. Explicitly compare multilayer and single-layer outcomes to quantify the degree of amplification that aggregation can hide. (See Sections 7 and 9.)
4. **Intervene** or mitigate through network structure, risk limits, and capital by: reducing common exposures in banks via rewiring portfolios; calibrating resolution and loss-absorbing tools to shock size with caps on TLAC and MREL cross-holdings [115–117], and tightening firm-level concentration and liquidity risk limits; strengthening non-bank resilience to procyclical margin and collateral dynamics by improving margining practices and requiring liquidity preparedness for margin and collateral calls, reducing forced sales and liquidity spirals under stress [6, 7]; and applying member-centred interventions across financial market infrastructures, including CCPs and product layers, targeting cross-layer bridge members with margining, participation limits, or concentration-based add-ons, because cross-layer participation can transmit stress across venues even when a single CCP appears locally contained [56, 62]. (See Section 9.)

10.3 Limitations and Priorities

The synthesis points in a clear direction: multilayer frameworks are relevant for policy and risk management decisions, but the evidence base is uneven and transferability across application settings depends on how networks are constructed, coupled, and stress tested. Three constraints recur: gaps in data coverage, designs that are static or weakly dynamic, and sensitivity to modelling choices. In practice, these limitations manifest as incomplete coverage of off-balance-sheet and non-bank exposures, reliance on single-period snapshots that preclude testing feedbacks over time, and sensitivity to methodological choices including rolling window length, backbone filtering, tail-risk estimator selection, and price-impact specification. A further recurring limitation is that interlayer coupling strengths and weights are rarely observed directly, so coupling is typically imposed or calibrated, and conclusions can shift with the chosen coupling scheme.

Establishing a replicability package should become a standard requirement. At the minimum, it should provide code and parameter files; a data dictionary; a transparent mapping from raw data to layers and edge weights; and a clear record of the layer schema, edge weighting rules, sparsification or backbone rule, window and horizon definitions, and interlayer coupling assumptions.

Immediate priorities should focus on auditability and on showing that core conclusions are not artefacts of model construction choices. This includes a replicability package plus robustness checks over a small number of plausible window lengths and backbone filters, with explicit sensitivity reporting for rankings and loss estimates. Stress tests should also incorporate explicit links to financial market infrastructures where data permit, and portfolio rewiring pilots should be evaluated with amplification comparisons.

Overall, evidence across these 112 studies supports a shift from single-layer proxies to multilayer mapping, monitoring, and stress testing, ensuring that financial stress is measured and managed through the channels through which it propagates in practice.

List of abbreviations

ACS	Average connectedness strength
AOD	Average overlap degree
ASEAN	Association of Southeast Asian Nations
BRICS	Brazil, Russia, India, China, South Africa
CASP	Critical Appraisal Skills Programme
CAViaR	Conditional Autoregressive Value at Risk (model)
CCP	Central counterparty
CDS	Credit default swap
CoVaR	Conditional Value at Risk (systemic risk measure)
DCC	Dynamic conditional correlation
DY	Diebold-Yilmaz spillover framework
EL	Expected loss
ES	Expected shortfall
ETF	Exchange-traded fund

EU	European Union
FEVD	Forecast error variance decomposition
FMI	Financial market infrastructure
FX	Foreign exchange
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GFC	Global Financial Crisis (2008-2009)
G-SIB	Global Systemically Important Bank
IFRS	International Financial Reporting Standards
IPR	Inverse participation ratio
LASSO	Least Absolute Shrinkage and Selection Operator
LPSI	Label-propagation source-identification
MREL	Minimum Requirement for own funds and Eligible Liabilities
MRIO	Multi-regional input-output
MST	Minimum Spanning Tree
NBFI	Non-bank Financial Intermediation
NCC	Network Correlation Coefficient
NCI	Network-wide Contagion Intensity
NODF	Nested overlap and decreasing fill (measure)
NVE	Network-only Volatility Effect
OTC	Over-the-counter
PMFG	Planar Maximally Filtered Graph
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QC-ISAM-ARMA	Quantile-coherency inter-slice aggregation autoregressive moving-average
QE	Quantitative Easing
SIS	Susceptible-Infected-Susceptible
SRC	Systemic risk contribution
TCI	Total Connectedness Index
TLAC	Total Loss-Absorbing Capacity
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TVP-SV-VAR	Time-Varying Parameter Vector Autoregressive model with Stochastic Volatility
TVP-VAR	Time-Varying Parameter Vector Autoregression
UK	United Kingdom
US	United States of America
VAR	Vector Autoregression
VaR	Value at Risk
VTN	Variance Tail Network

11 Declarations

Availability of data and materials

Not applicable. No datasets were generated or analysed during the current study.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

JS: Conceptualisation, methodology, writing, draft preparation. TO-E: Writing, review and editing, supervision. All authors read and approved the final manuscript.

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Appendix A Supplementary Methodological Details

This appendix provides extended methodological details supporting the systematic review protocol summarised in Section 2.

A.1 Scope and Time Frame Rationale

The definition of financial systems was deliberately broad to include both traditional financial markets and extended economic networks with financial characteristics, such as global trade, supply chains, and policy frameworks governing these systems. The time frame was selected to capture the period following the establishment of foundational multilayer network theory in the early 2010s, and to extend beyond the broad review conducted in 2014 by [128] and by [129], whilst encompassing recent developments in the field.

A.2 Database-Specific Search Strategies

The systematic search was conducted across ten databases. Table A1 presents the full search strings adapted to each database's syntax and field restrictions.

A.3 Detailed Eligibility Criteria

A.3.1 Inclusion Criteria (Extended)

Studies were included if they met all of the following criteria:

(a) **Primary focus on multilayer networks**: The study must employ multilayer, multiplex, interdependent, or temporal network methodologies as the principal analytical framework, rather than as a peripheral or illustrative component.

(b) **Financial systems application**: The financial systems examined must fall within the scope defined in Subsection 2.2, encompassing banking and capital

Table A1: Database-specific search strings

Database	**Search String**
Web of Science Core Collection	TS=((”multilayer*” OR ”multiplex*” OR ”network of networks” OR ”temporal network*” OR ”multi-layer*” OR ”interdependent network*” OR ”multilevel*”) AND (”financ*” OR ”bank*”))
Scopus	TITLE-ABS-KEY ((”multilayer*” OR ”multiplex*” OR ”network of networks” OR ”temporal network*” OR ”multi-layer*” OR ”interdependent network*” OR ”multilevel*”) AND (”financ*” OR ”bank*”))
IEEE Xplore	((”multilayer*” OR ”multiplex*” OR ”network of networks” OR ”temporal network*” OR ”multi-layer*” OR ”interdependent network*” OR ”multilevel*”) AND (”financ*” OR ”bank*”))
JSTOR	(multilayered* OR multiplex (AND network*))
EBSCO Academic Search Complete	AB (”multilayer*” OR ”multiplex*” OR ”network of networks” OR ”temporal network*” OR ”multi-layer*” OR ”interdependent network*” OR ”multilevel*”) AND AB (”financ*” OR ”bank*”)
arXiv	Advanced search fields abstract: multiplex OR multilayer; then AND abstract=finance OR bank
SSRN	Used singular terms: first ”multiplex” and ”multilayer”, then search within the resulting papers for terms ”network” then ”finance” or ”financial”
RePEc	(multilayer* — multiplex — ”multi-layer*”) + (network*) + (financ* — bank*) ”perceptron”
Google Scholar	(allintitle: network multi multilayer OR multiplex OR bank OR finance OR financial -neural -algorithm -perceptron)
Semantic Scholar (Ai2 Paper Finder)	Input query: ”Papers applying either multilayered networks, multiplex, or multi-layers, to financial networks and finance systems”

markets, payment and settlement systems, corporate finance linkages, and macro-financial structures (including trade, supply chains, and policy frameworks) when these directly shape financial propagation channels.

(c) **Publication window**: Published or accepted for publication (in press with a DOI) between 1 June 2015 and 31 May 2025.

(d) **Publication type**: Peer-reviewed journal articles, book chapters, or conference proceedings. Working papers were excluded unless subsequently published in peer-reviewed form, in which case the peer-reviewed version was used.

(e) **Citation threshold (pragmatic screen)**: For studies published up to and including 2023, a minimum of five citations at the time of screening was required as a light-touch indicator of scholarly uptake. No citation threshold was applied to studies published in 2024 or 2025, recognising that citation counts are immature for recent work.

(f) **Empirical or conceptual validation**: The study must provide either empirical validation using real-world or simulated data, or conceptual validation through formal theoretical development.

A.3.2 Exclusion Criteria (Extended)

Studies were excluded if they met any of the following criteria:

(a) **Methodological focus without financial application**: Studies developing machine learning algorithms, software tools, or network methods without substantive application to financial systems. We excluded the term 'perceptron' to reduce false positives from neural network papers using multilayer perceptrons.

(b) **Non-peer-reviewed formats**: Preprints (unless subsequently published), retracted papers, working papers, review papers, meta-analyses, commentaries, editorials, and thesis publications.

(c) **Insufficient validation**: Studies lacking empirical validation or practical application to financial contexts.

(d) **Language**: Publications not available in English.

Central bank and international organisation reports were treated as grey literature and cited only when they provide data or policy context rather than core empirical findings.

A.4 Study selection workflow and stage-specific counts

Our selection process involved four stages. In the initial stage, the search yielded 1,124 potentially eligible papers after removing duplicates within each database. Although the initial search targeted finance-related terms, abstract screening showed many uses of multilayer terminology in non-financial contexts, for example biology and social networks, so a second stage applied finance-specific inclusion and exclusion rules to refine the pool through comprehensive abstract screening and selective full-text examination.

Inclusion and exclusion criteria, including the citation threshold rule, are reported in Appendix A.3.

The screening process involved systematic examination of abstracts and targeted full-text searches for relevant terminology. This procedure reduced the initial pool of 1,124 papers to a preliminary selection of 208 that met the specified criteria.

The third stage reconciled results across databases, further reducing the number of papers from 208 to 106 unique publications after cross-database deduplication. Six additional papers were identified through reference list examination, giving a final total of 112 papers. The fourth and final stage was the synthesis of all 112 selected papers.

A.5 Quality Assessment Framework

Quality assessment was informed by an adaptation of the Critical Appraisal Skills Programme (CASP) framework [17]. Given the heterogeneity of study designs spanning empirical analyses, simulations, and theoretical contributions, the framework was applied flexibly rather than as a scoring instrument, and we did not compute an aggregate score. The following dimensions were assessed where available and relevant:

1. **Research question clarity**: Is the research question or objective clearly stated?
2. **Methodological appropriateness**: Is the multilayer network methodology appropriate for the research question?
3. **Data quality and transparency**: Are data sources, collection methods, and any limitations clearly described?
4. **Network construction transparency**: Are layer definitions, edge weighting rules, and any sparsification or filtering procedures clearly specified?
5. **Analytical rigour**: Are the analytical methods applied correctly and are assumptions stated?
6. **Robustness and sensitivity**: Are results tested for sensitivity to key parameter choices (e.g., window length, backbone thresholds)?
7. **Replicability**: Is sufficient detail provided to allow replication?
8. **Limitations acknowledgement**: Are limitations of the study design and data clearly acknowledged?

A.6 Data Extraction Template

The following information was extracted from each included study using a standardised template:

1. Bibliographic details (authors, year, journal, DOI)
2. Application domain (one of six domains: Bank–firm Networks, Corporate Networks, Global Trade and Supply-Chain Networks, Interbank Networks, Financial Markets, and Global Systemic Risks)
3. Network model classification (multiplex, multilayer, interdependent, temporal, hybrid)
4. Layer architecture (node types, edge definitions, number of layers, interlayer coupling)
5. Mathematical formalism (e.g., supra-Laplacian, tensor, supra-adjacency matrix)
6. Data sources and sample characteristics (geography, time period, sample size)
7. Key findings (including reported magnitudes, benchmarks, comparisons with single-layer baselines)
8. Methodological quality indicators
9. Limitations acknowledged by authors
10. Limitations identified during review
11. Future research directions suggested

A.7 Software and Tools

Reference management and deduplication were conducted using Zotero (version 6.0). Search results, screening decisions, and data extraction were recorded in Microsoft Excel. No automated screening tools were used; all screening was conducted manually by the lead author to ensure consistent application of eligibility criteria across the interdisciplinary literature.

Appendix B Cross-cutting Diagnostics, Methodological Extensions, and Illustrative Applications

B.1 Introduction

Three studies show how multilayer analysis extends beyond balance-sheet and price data to capture information flows, sentiment, and organisational influence. Although these three applications sit outside the six core financial categories in the main text, they illustrate the versatility of multilayer diagnostics in non-balance sheet settings.

The three studies are: a media–country multiplex linking financial news to geography, trade, and CDS correlations [130], a bank–media multiplex linking bank co-mentions to sentiment tone [131], and a lobbying multiplex linking organisations through formal and relational ties in the European Union (EU) [132].

B.2 Data and layer architecture

In the media–country setting, the nodes are 50 countries. Two news-based layers are built from more than 1.3 million financial articles aggregated via 2,503 RSS feeds from 170 sites (November 2011 to December 2013): a co-occurrence layer and a sentiment layer. The sentiment layer is separated into positive and negative snapshots. These two news-based layers are compared with three empirical layers, geography, trade, and credit default swap (CDS) correlations, forming a five-layer system. Trade and CDS links are only included when they exceed predefined statistical thresholds [130].

The bank–media multiplex covers 214 Chinese banks, with two sentiment layers constructed from Baidu News and EastMoney (January 2018 to December 2019). Edges are undirected and weighted by monthly co-mentions, with a corpus of 152,994 co-mention records; results are reported per layer and for the aggregate (union) network [131].

The lobbying multiplex contains four layers: affiliations, shareholdings, common directors (interlocking directorates), and client relationships, across 6,637 organisations in the EU Transparency Register [132]. The interlocking directorate layer is undirected, while the other layers are directed, with weights available for shareholding and client ties in the underlying data [132].

B.3 Methods, in brief

All three papers adapt standard diagnostics to multilayer settings. The media–country study compares layer pairs using link overlap, compares central nodes using eigenvector centrality, reports precision at k (a top k retrieval accuracy measure), and applies k-core analysis across the five-layer set [130]. The bank–media study reports small-world indicators, average path length and clustering, for each layer and for the aggregate [131]. It also reports node strength, participation coefficients, inter-layer strength correlation, and Jaccard similarity between tone layers. The lobbying study computes per-layer clustering, path length, assortativity, and a multiplex centrality measure incorporating feedback dynamics, then relates degree and centrality to financial metrics [132]. Centrality is defined as a PageRank-style feedback process in which a node's in-centrality depends on the centrality and relative lobbying expenditure of its in-neighbours, and out-centrality is obtained by reversing edge direction. The multiplex version then computes centrality using information from multiple link types at once, so prominence can increase when an organisation is well connected in one layer even if it is less connected in another [132].

B.4 Mechanisms and comparative findings

Media-derived links align most strongly with geography and trade, rather than with CDS spread correlations, which are computed over three-month windows. Co-occurrence links align most closely with geography, whilst positive sentiment aligns more closely with trade. Overlap with the CDS correlation layer is lowest. Countries that frequently appear in the overlap core between the positive sentiment and trade layers include China, Germany, the United States, the United Kingdom, Japan, Brazil, France, and Australia. Germany appears in the overlap core between the positive sentiment and geography layers in 23 of the 26 sample months [130].

Bank attention networks built from co-mentions exhibit short average path lengths and high clustering. The mixed (aggregate) network shows an average path length of 1.624 and clustering coefficient of 0.816, with annual values of 1.804/0.789 (path length/clustering) in 2018 and 1.626/0.835 in 2019. Inter-layer similarity between positive and negative tone layers is low when measured by Jaccard overlap of edges, yet inter-layer strength correlation is high, indicating that the same banks tend to be prominent across both tones even when the specific edges connecting them differ [131].

In the lobbying multiplex, network position and degree correlate moderately with lobbying expenditure in the affiliation layer (out-degree) and the interlocking layer (degree), but these associations are weak in the shareholding layer. Pearson correlation coefficients between lobbying expenditure and out-degree are 0.46 in the affiliation layer and -0.15 in the shareholding layer, while the correlation between lobbying expenditure and degree is 0.52 in the interlocking layer; the correlation between client in-degree and turnover is 0.67. For centrality measures, correlations with lobbying expenditure are 0.172 for in-centrality in affiliation and 0.074 for out-centrality in the multiplex. These correlations suggest that financial resources and network position are related, but budget alone is an unreliable proxy for degree or centrality [132].

B.5 Limitations

Text-derived layers depend on corpus coverage, threshold choices, and temporal windows [130]. The bank–media multiplex proxies for attention and tone rather than balance-sheet liquidity and also spans a short window [131]. The lobbying register is self-reported and heterogeneous across actor types, and some layers are weighted by construction, but are analysed using unweighted, or undirected, snapshots [132]. Furthermore, data sources used in [132] do not provide historical information, therefore only a single snapshot at a time can be studied.

Collectively, these cross-cutting applications illustrate how multilayer diagnostics transfer to text and organisational data: media layers align more with geography and trade than with CDS comovement, bank sentiment networks exhibit small-world properties with short paths and high clustering, and network position correlates only moderately with lobbying expenditure across layers. Methods and observation windows are constrained by data availability, and some layers are treated as unweighted, so magnitudes should be interpreted with caution. Within those constraints, the diagnostics are informative and replicable within their stated designs [130–132].

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