Networks in Finance: Foundations and Frontiers

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Abstract

Networks in finance shape how value is created and risks emerge, both systemic and systematic. We survey how different networks, including production, banking, directors, and information networks, propagate micro shocks and transmit them to broader levels of aggregation. First, we synthesize the literature on the efficiency-stability trade-off governing systemic risk: interconnections transmit gains, liquidity, and knowledge, but create channels for contagion. Beyond the foundational focus on within-network transmission, we extend the discussion to across-networks spillovers. Second, moving from systemic to systematic risk, we show how network topology drives the stochastic discount factor, affecting factors and expected returns. We also trace how networks form and evolve, dynamically generating new sources of risk. By adopting a macro perspective that unifies distinct networks into an overarching network-of-networks (meta-network), we focus on shared propagation mechanisms and outline directions for future research, including how networks may evolve with the rise of AI, intangibles, and deglobalization.

Contents

1. Introduction

Over the past two decades, financial economics has increasingly utilized network analysis to study interconnected markets and institutions. The first wave of studies focused on banking networks, showing how balance-sheet linkages transmit shocks and amplify systemic risk (see, e.g., Allen & Gale 2000, Eisenberg & Noe 2001). A parallel literature in macroeconomics then established that asymmetric production networks can transform micro disturbances into aggregate fluctuations, making network topology a first-order determinant of business-cycle dynamics (see, e.g., Acemoglu et al. 2012, Carvalho 2014). Since then, the network perspective has extended into investor portfolios, where economically linked firms exhibit predictable return comovement (see, e.g., Cohen & Frazzini 2008, Ali & Hirshleifer 2020), and into corporate governance, where influence networks affect firms' policies (see, e.g., Fracassi & Tate 2012, Cai & Szeidl 2018).

Today, network tools inform core questions in financial economics. Traditional models assumed that idiosyncratic events were diversifiable, that systematic risks arose only from aggregate shocks, that risk exposures were fixed or depended purely on corporate policies, and that firms and intermediaries were ex-ante homogeneous and independent or randomly matched. The network view changed these assumptions, explaining when and how local shocks can become systemic, how to measure systemic importance beyond isolated firm characteristics, what microfounds systematic risk, why a firm's position in the network determines its risk exposures beyond investment choices, how resilience depends on network topology, and why regulation and market design must internalize spillovers across different sectors and networks. In short, networks have become a broad analytical tool for understanding macroeconomic volatility, asset pricing, and corporate-finance policies.

This review takes a distinct unifying approach. We adopt a macro perspective that views the economy as a *meta-network* of interacting networks (e.g., production, banking and funding, directors, and information). Within this approach, our organizing theme is propagation: how links both within and across networks form and transmit shocks, when propagated shocks turn from micro-level disruptions to macro-level fluctuations, and how these forces affect valuation. This macro focus distinguishes this review from prior surveys. Allen & Babus (2009) survey early applications of network theory to financial systems and interbank markets, while later systemic-risk surveys focus more directly on financial contagion, intermediation, and regulation (see, e.g., Summer 2013, Glasserman & Young 2016, Jackson & Pernoud 2021). We build on these foundations but shift the core question from how fragile a *financial* network is to how *heterogeneous* networks transmit shocks, make some shocks priced, and change risk.[1]

The transition from a micro- to a macro-approach is achieved through five contributions. First, we categorize the main networks in finance, emphasizing for each the core economic gains that justify its existence and the systemic-risk trade-offs implied by its topology. Second, we map how these networks interact both within and across them, tracing the transmission channels that drive contagion and amplification, and summarizing the macroprudential tools that target those channels. Third, moving from systemic to systematic risk, we show how network-driven forces enter the stochastic discount factor, through concentration, sparsity, and centrality, thereby shaping expected returns. Fourth, we review how networks endogenously form and why individual nodes might fail, highlighting the drivers of network fragility. Finally, we draw on these insights to outline directions for future research.

Finance as a Natural Laboratory for Network Analysis

Finance provides a rich setting for network analysis because of its granular, high-frequency data. Financial markets generate transaction-level records on trades, contracts, and positions, far more detailed than the aggregate low-frequency data typical in macroeconomics. Many financial networks, such as interbank lending, derivative exposures, credit chains, or equity ownership ties, are directly observable or can be reconstructed from disclosures and databases, allowing researchers to map networks at fine scales and track their evolution over time.

A further advantage is the real-time information incorporated into financial markets. Shocks such as earnings surprises, defaults, or policy announcements provide natural experiments: forward-looking prices of connected firms and intermediaries adjust within minutes. These high-frequency reactions make it possible to cleanly isolate network propagation, unlike macroeconomic data, where effects unfold slowly and are confounded by overlapping shocks.

Finance features a broad range of linkages: real, financial, and contractual. This variety enables researchers to study how shocks transmit simultaneously across channels, often amplifying propagation relative to a standard production economy with risk neutrality.

Finally, finance can draw on well-developed asset-pricing tools to assess the welfare implications of network structures by tracing how networks affect investors' marginal utility (i.e., the stochastic discount factor). However, this is not the only welfare

[1]The aim of this survey is to connect networks, not to rebuild the microfoundations of each. Readers seeking further information on a particular network should treat our citations as a guide into that literature.

metric. Corporate-finance and banking emphasize real costs, including bankruptcy losses, inefficient liquidation, and investment distortions. We use the SDF metric for systematic risk and valuation, and the real-cost metric for systemic failures and policy.

The rest of the survey is organized as follows. Section 2 sets notations, introduces a workhorse network tool, and outlines the meta-network map. Section 3 analyzes systemic risk, connecting it to specific network structures and to the meta-network. Section 4 analyzes systematic risk, connecting network structures to the stochastic discount factor and expected returns. Section 5 studies endogenous network formation and fragility. Section 6 outlines open questions and hypotheses.

2. Networks in Finance: Preliminaries

2.1. Types of Networks and Their Interconnection

Institutions and financial markets are linked through a wide variety of relationships: trade (supplier–customer chains), ownership (securities cross-holdings), contractual obligations (creditor–debtor ties, derivative exposures), and social ties (shared investors, common decision makers). These relationships can be directed (when a connection is "one-way") or undirected (when a connection is "two-way"). When aggregated by type, links constitute different networks:

(i) *Production and real-side firm networks*: A production network refers to directed supplier–customer flows of goods and services used in production. These links transmit supply and demand shocks along input–output chains. However, business units can also be connected using other real-side distinct channels, such as trade credit that finances supplier–customer flows and internal plant networks within multi-plant firms. Additional real-side ties among nonfinancial firms include competition, product similarity, and R&D alliances.

(ii) *Banking and Over-the-Counter (OTC) networks*: capture connections between intermediaries, which can be directed (e.g., Fed funds loans, syndicated loans) or undirected (e.g., signing an ISDA Master Agreement to facilitate OTC trading). These links create channels for financial contagion, as distress in one intermediary can impair its counterparties.

(iii) *Investor and funding networks*: capture connections between institutional investors, mutual funds, pension funds, private equity, venture capital firms, hedge funds, sovereign wealth funds, and family offices. Connections may be direct (e.g., funding, ownership) or indirect (e.g., competition, co-location, shared directors, overlapping investor bases). Common ownership can generate correlation in asset prices and governance.

(iv) *Director and social networks*: capture connections between directors or executives, which can be directed (e.g., mentorship, influence) or undirected (e.g., friendships, colleagues, former classmates, neighbors). These ties facilitate coordinated policies.

(v) *Informational networks*: capture connections between different types of economic agents via direct and indirect information flows. For example, households share information about investment opportunities, consumer products, and risks using directed links (e.g., following someone on social platforms) and undirected links (e.g.,

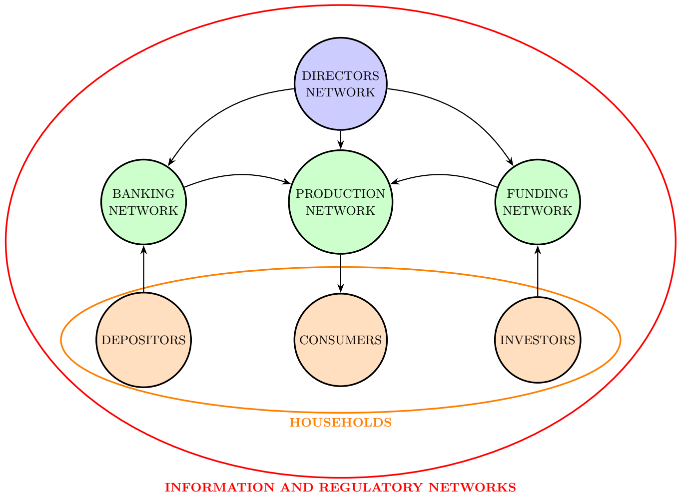

Figure 1: Meta-network in finance

friendships, neighbors, colleagues, co-investors, co-depositors).

Importantly, the networks above overlap and interact. Figure 1 provides a schematic illustration of a *meta-network* in finance. The meta-network is a network-of-networks in which nodes are individual networks in finance that we listed above. The meta-network has two types of links. The intra-network links that connect agents in each network (see examples above), and inter-network links that capture interaction between nodes that belong to different networks. The inter-network links capture interactions between economic agents both in normal times and during crisis. Below we provide examples for inter-network links.

Meta-network: A network-of-networks with *intra-network* links within each network (production, banking, funding, directors, social, information, and regulatory) and *inter-network* links across networks.

Directors serve on boards of both financial (banks, funding firms, special purpose acquisition companies) and non-financial firms, creating directed ties between the social network and either financial or production networks. The banking network connects to the production network via loans that banks provide to corporations, either directly or through syndicates. The funding network connects to the production network via capital flows.

Households (excluding managers) interact with the networks above: as depositors, they underpin the banking network. As investors, they fuel the funding network. As consumers, they purchase final goods from the production network (and also supply labor). Households themselves are interconnected through social interactions.

Two related structures overlay the rest. First, interactions within and across networks are subject to regulation by a network of regulatory agencies (e.g., the Federal Reserve, the Federal Deposit Insurance Corporation, the Securities and Exchange Commission, the Financial Industry Regulatory Authority). Second, information networks connect all agents in the meta-network, with important implications for efficiency and risk.

2.2. Network Representation and Measurement

A network is defined by a set of nodes N connected through edges. We distinguish between two matrices. The raw weighted matrix $\widetilde{\mathbf{W}}_{N\times N}$ records dollar flows, exposures, or tie strength. The matrix $\mathbf{W}$ is the row-normalized weighting matrix, so every row (with at least one link) sums to one. Its entries are exposure shares, input shares, or attention weights, depending on the application. In general, $\mathbf{W}_{ij} > 0$ indicates a directed link through which node j can affect node i. Unless noted otherwise, $\mathbf{W}$ is the matrix used in propagation equations and $\widetilde{\mathbf{W}}$ denotes raw flows or exposures.

The economic interpretation of these entries depends on the network type. In production-network applications, we use the convention that $\widetilde{\mathbf{W}}_{ij}$ is the raw flow of goods from node j to node i, and $\mathbf{W}_{ij}$ is the share of node i's intermediate inputs sourced from supplier j, so each row of this supplier-share matrix sums to one. In financial networks, $\widetilde{\mathbf{W}}_{ij}$ may measure the dollar exposure of bank i to counterparty j, while $\mathbf{W}_{ij}$ is the exposure share. In investor networks, $\widetilde{\mathbf{W}}_{ij}$ may denote the dollars of firm i held by investor j. In information or social networks, $\widetilde{\mathbf{W}}_{ij}$ can capture co-mentions, communication intensity, shared directorships, geographic proximity, or attention flows, with $\mathbf{W}$ converting those intensities into propagation weights.

Some of these networks are easier to observe than others. Regulatory filings and industry datasets often disclose direct relationships: banks report syndicated loans, public companies must disclose major customers under accounting standard SFAS 131, and board memberships or large equity holdings appear in mandatory filings.

In other cases, networks must be inferred from other observables using various econometric tools (e.g., structural estimation using SMM as in Gofman 2017, text-based methods as in Hoberg & Phillips 2016, news-based methods as in Schwenkler & Zheng 2020, Hilt & Schwenkler 2024, or statistical inference as in Billio et al. 2012, Diebold & Yılmaz 2014): correlated prices, common investors, or news co-mentions are used to proxy connections even when no explicit contract exists.[2]

Once $\mathbf{W}$ is mapped, a growing methodological toolkit quantifies concepts such as path length, centrality, and clustering in a financial context. Such properties help explain how shocks propagate, as we explore next.

2.3. Workhorse Tool: Spatial Autoregressions and Network Effects

A common empirical approach in networks is the use of spatial autoregressive (SAR) models to capture peer effects and shock propagation, building on spatial econometrics (Cliff & Ord 1981, Anselin 1988, LeSage & Pace 2009). In these models, an outcome for a given node (e.g., a firm's return, a default indicator, or a balance-sheet outcome) is regressed on the outcomes of its network neighbors, providing a reduced-form way to detect contagion or diffusion through linkages. The structure is especially useful when theory maps the weighting matrix to input–output shares, counterparty exposures, or ownership links (Ozdagli & Weber 2026, Di Giovanni & Hale 2022).

A canonical specification can be written as:

$$\mathbf{y}_t = \rho \mathbf{W} \mathbf{y}_t + \mathbf{X}_t \beta + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\mathbf{0}, \sigma_t^2 \mathbf{I}), \tag{1.}$$

where $\mathbf{y}_t$ is an $N \times 1$ vector of outcomes, $\mathbf{W}$ is the network weighting matrix, ρ is the scalar transmission coefficient measuring how strongly outcomes comove along the links in $\mathbf{W}$, $\mathbf{X}_t$ is a matrix of exogenous controls with coefficient vector β capturing direct, non-network

[2]Increasingly, commercial databases estimate $\mathbf{W}$ directly or indirectly with greater granularity: FactSet Revere for supply chains, BoardEx for executive ties, and World Input-Output Database (WIOD) for international flows.

exposure, and $\boldsymbol{\varepsilon}_t$ is a vector of shocks, usually assumed to be independent across nodes. A significantly positive ρ estimate indicates that linked nodes move together beyond what their direct exposures captured by β would predict, consistent with shock propagation.

The choice of $\mathbf{y}$ varies with the type of network $\mathbf{W}$ in Figure 1: for production networks, it can be industries' output or returns; for banking networks, it can be an indicator of default or a distress metric; for social or director networks, it can be any firm-level policies such as R&D or executive compensation; for information networks, it can be a measure of price momentum or volatility.

This simple tool yields a transparent benchmark for linear propagation. Let the network multiplier be $\mathbf{L}(\rho) = (\mathbf{I} - \rho\mathbf{W})^{-1}$. Because $\mathbf{W}$ is row-normalized, the series $\mathbf{L}(\rho) = \mathbf{I} + \rho\mathbf{W} + \rho^2\mathbf{W}^2 + \cdots$ converges when $|\rho| < 1$. The term $\mathbf{W}^k$ collects all directed walks of length k. Thus a shock to a node first affects directly linked nodes, then nodes two links away, and so on, with path weights scaled by powers of ρ. As $|\rho|$ approaches one from below, long paths fade out more slowly.

In finance applications, the SAR model can sometimes be given a structural interpretation. One might interpret y_{it} as the response of firm i's cash flow, return, or distress probability to a shock, including indirect effects transmitted through the network. Network propagation can turn idiosyncratic shocks into systemic and even systematic risk when a shock travels through $\mathbf{W}$ and affects many other nodes.

2.3.1. Properties of Nodes in a Network Nodes can be characterized by various properties, originally developed in graph theory (see, e.g., Newman (2018)). We introduce a small set of measures used repeatedly in the survey. Each answers one economic question: who can spread shocks, who is exposed to them, and which nodes aggregate micro shocks into macro risk.

At the most local level, degrees and strengths summarize a node's immediate reach and exposure. Let the unweighted adjacency matrix $\mathbf{A} = (A_{ij})$ be given by $A_{ij} = \mathbf{1}_{W_{ij}>0}$. The out- and in-degrees, $d_i^{\text{out}} = \sum_j A_{ji}$ and $d_i^{\text{in}} = \sum_j A_{ij}$, count how many direct partners i can affect and how many can affect i. The corresponding out- and in-strengths, $s_i^{\text{out}} = \sum_j \widetilde{W}_{ji}$ and $s_i^{\text{in}} = \sum_j \widetilde{W}_{ij}$, quantify the intensity of those ties. Economically, these four quantities give the first-order "strength of spillover": with larger s_i^{out}, a given impulse at i has more weight to spread outward, while larger s_i^{in} means i has more receiving capacity for shocks arriving from elsewhere. They also capture diversification or specialization at the node margin. For example, in a production network where out-links point to customers, a higher d_i^{out} typically means demand is diversified across more buyers and idiosyncratic customer shocks average out more.

Out-/In-degree:
$d_i^{\text{out}} = \sum_j A_{ji}$,
$d_i^{\text{in}} = \sum_j A_{ij}$

Out-/In-strength:
$s_i^{\text{out}} = \sum_j \widetilde{W}_{ji}$,
$s_i^{\text{in}} = \sum_j \widetilde{W}_{ij}$

At a more global level, centrality measures summarize each node's position in the network and its potential role in economy-wide shock transmission. Recall our convention that $W_{ij} > 0$ means that node j can affect node i. Eigenvector centrality gives node i a high score when the nodes that source from, or are exposed to, i are themselves central:

$$c = \chi^{-1}\mathbf{W}^\top c.$$

Because $\mathbf{W}$ is row-normalized, the largest eigenvalue is $\chi = 1$. Equivalently, $c_i = \sum_j W_{ji}c_j$, so node i is central when important nodes depend on it. Following Ahern (2013), the row-normalized network can be viewed as a Markov chain, and c_i can be interpreted as the stationary share of time a shock moving through the network spends at node i. High-c_i nodes are more likely to lie on the path of shocks that travel through the economy, making

Eigenvector centrality: $c = \chi^{-1}\mathbf{W}^{\top}c$

them potentially more exposed to aggregate risk. Alternative notions of centrality may be more appropriate depending on the assumed propagation mechanism. See Borgatti (2005) for a detailed discussion.

The next three measures: upstreamness, downstreamness, and the Domar weight, are specific to production networks. The first two capture vertical position, useful for systemic and systematic risk analysis as well as for corporate-finance policies. Let $\mathbf{\Theta}$ denote the Ghosh (output–coefficient) matrix.[3] Antràs et al. (2012) define *Upstreamness* as the average forward distance of a node's output from final demand:

Upstreamness: $U = (\mathbf{I} - \mathbf{\Theta})^{-1}\mathbf{1}$

$$U \;=\; (\mathbf{I} - \mathbf{\Theta})^{-1}\mathbf{1}.$$

To define downstreamness and the Domar weight below, we use the standard input-coefficient matrix rather than the row-normalized supplier-share matrix. Let $\mathbf{\Omega} = \mathrm{diag}(\mathbf{m})\mathbf{W}$, where m_i is node i's intermediate-input share and $\Omega_{ij} = m_i W_{ij}$ is the value of input j used per dollar of node i's gross output.[4] Miller & Temurshoev (2017) define *Downstreamness* as the average backward distance of a node's production from primary inputs:

Downstreamness: $D = (\mathbf{I} - \mathbf{\Omega})^{-1}\mathbf{1}$

$$D \;=\; (\mathbf{I} - \mathbf{\Omega})^{-1}\mathbf{1}.$$

Here $\mathbf{1}$ is the all-ones vector. Intuitively, a sector with high U_i is far from final demand: its output is embodied in many production stages before reaching consumers. A sector with high D_i uses inputs that themselves embody many prior production stages, so it is downstream relative to primary factors; this does not mechanically imply that it is close to final demand. Supply shocks typically originate upstream and propagate downstream through relative prices, while demand shocks originate near final consumers and propagate upstream through quantities. Thus, broadly speaking, U is useful for studying exposure to demand-side shocks, whereas D is useful for studying exposure to supply-side shocks.[5]

Domar Weight: $\Delta_i = \sum_j \varphi_j[(\mathbf{I} - \mathbf{\Omega})^{-1}]_{ji}$

The classical *Domar weight* of node i is its gross sales as a share of GDP, $\Delta_i \equiv \frac{p_i x_i}{\mathrm{GDP}}$. Market clearing links this definition to the production network. Let φ_j denote sector j's final-demand share of total GDP. With the input-coefficient matrix $\mathbf{\Omega}$, $\Delta_i = \sum_j \varphi_j \big[(\mathbf{I} - \mathbf{\Omega})^{-1}\big]_{ji}$, so node i's Domar weight aggregates all direct and indirect paths from its output to final demand.[6] A large Domar weight means that shocks originating in i have a strong aggregate impact, making such nodes natural sources of systematic risk.[7]

[3] For forward (supplier→customer) traversals we use the Ghosh/output–coefficient matrix $\mathbf{\Theta}$, with entries $\theta_{ij} \equiv \frac{\text{intermediate sales from } i \text{ to } j}{\text{gross output of } i}$. Hence $\sum_j \theta_{ij}$ is the share of i's output sold to intermediate users, and $1 - \sum_j \theta_{ij}$ is the share sold directly to final demand.

[4] The remaining $1 - m_i$ accrues to value added or primary factors. Thus the rows of $\mathbf{\Omega}$ sum to less than one, making $(\mathbf{I} - \mathbf{\Omega})^{-1}$ well defined.

[5] When link strengths are unavailable, upstreamness can be defined as the directed shortest-path distance to final-good producers (Gofman, Segal & Wu 2020). Let $\mathcal{C}$ be the set of consumption-good producers and let $\mathcal{D}(i,j)$ be the shortest directed distance from i to j. Then $U_i = \min_{j\in\mathcal{C}} \mathcal{D}(i,j)$. Gofman & Wu (2022) expand this methodology to decompose a production network into individual supply chains.

[6] In efficient economies, Hulten's theorem implies that this same object measures the first-order effect of a productivity shock at node i on aggregate output. This first-order relation holds exactly in the Cobb–Douglas benchmark of Long Jr & Plosser (1983) and Acemoglu et al. (2012), in which expenditure shares are invariant to shocks. Beyond the first order, nonlinearities, complementarities, and distortions mean that Domar weights need not be sufficient statistics for aggregate effects

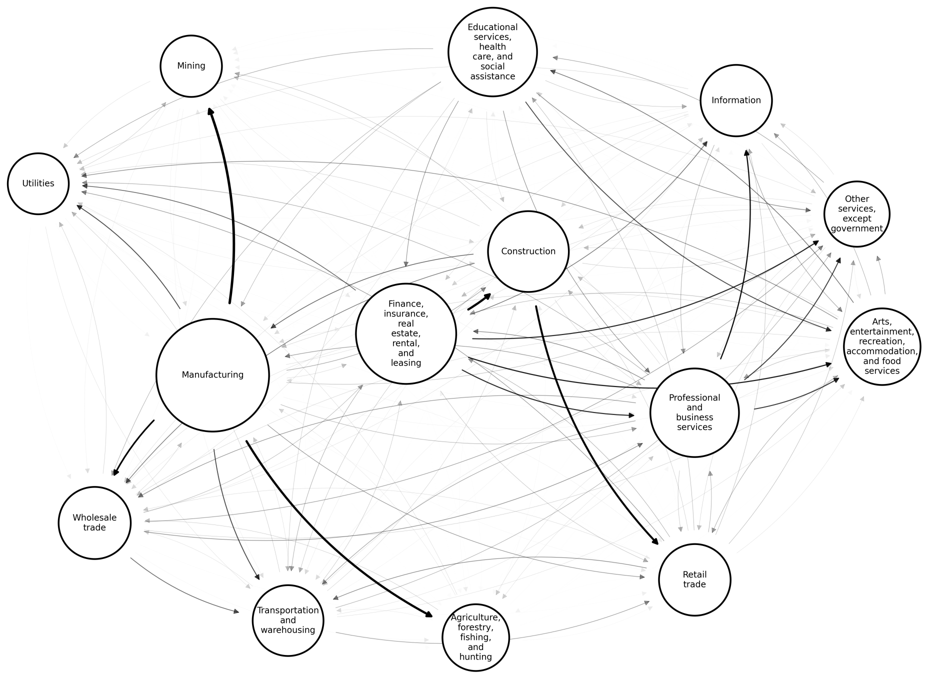

Figure 2: US Production Network at the Sector Level

The figure shows a weighted directed network representing the flows of inputs supplied by one sector to another. Nodes represent different sectors, and edges represent flows of inputs, excluding within-sector input supply. We construct the supplier–buyer revenue share matrix using the Bureau of Economic Analysis (BEA) MAKE and USE tables for 2024. The MAKE table reports the value of each commodity produced by each industry, while the USE table reports the value of each commodity used as an intermediate input by each industry. First, we compute each industry's share of production for a given commodity as its value in the MAKE table divided by the total production of that commodity across all industries. We then multiply this production share by the corresponding commodity use values from the USE table and sum across all commodities to obtain bilateral revenue flows between supplier and buyer industries. Finally, we normalize each supplier's revenue flow by the total intermediate input use of the buyer industry, yielding the supplier's revenue share in the buyer industry's total inputs. The resulting network of suppliers' share captures the fraction of each industry's inputs sourced from every other industry, and is visualized as a weighted direct network. The intensity of an arrow from node i to j shows how much sector j is buying from i relative to other suppliers.

Example: U.S. Production Network and Nodes' Properties

Figure 2 presents a snapshot of the U.S. production network at the sector level as of 2024, based on BEA I/O tables. An arrow from sector j to sector i means that

(Hulten 1978, Baqaee & Farhi 2019).

[7]Stress periods can reorder which nodes matter. Dew-Becker (2023) defines a sector's *tail centrality* as a systemic-risk measure in nonlinear production networks, capturing downstream closeness to final production under complementarities and identifying sectors that matter most for disasters. It coincides with the Domar weight in the linear benchmark, but under strong complementarities it ranks the sectors that drive disasters, which need not be those that matter on average.

j sells intermediate inputs to i, and the intensity of the arrow indicates how much i buys from j relative to other suppliers. Finance, Manufacturing, and Construction stand out as central under this intermediate-input normalization, whereas retail trade and utilities are more peripheral. Manufacturing has high out-strength: it is a major supplier for mining, agriculture, and wholesale trade. The figure only shows the flow of intermediate inputs: The retail–wholesale relationship, for example, is less visually prominent because edges capture normalized direct intermediate-input shares, not final distribution margins or consumer-facing trade flows.

2.3.2. Properties of Network Structures. The network structure shapes the breadth and strength of how shocks travel. One dimension is the distribution of edges. For example, density, the share of present links $\frac{\sum_{i\neq j}\mathbf{1}\{W_{ij}>0\}}{N(N-1)}$, signals how many distinct connections exist. Economically, denser systems offer more opportunities for diversification (as idiosyncratic shocks have many paths to propagate) and more redundancy when a particular link fails. Sparse systems, by contrast, point to specialization: activity concentrates on few ties. That specialization can raise efficiency and help localize small shocks, yet it also makes the remaining ties load-bearing, so their disruption has a severe impact. Global sparsity can be measured via the average negative entropy of nodes' link weights, such as input shares in a production network, $\text{NS} = \sum_i \pi_i \sum_j W_{ij}\log W_{ij}$, where π_i denotes node i's share of total network size, for example, its output or sales share in a production network (Herskovic 2018). This size-share weight is distinct from the final-demand share φ_j used in the Domar-weight formula above.

Density: $\frac{\sum_{i\neq j}\mathbf{1}\{W_{ij}>0\}}{N(N-1)}$

Sparsity: $\sum_i \pi_i \sum_j W_{ij}\log W_{ij}$

Concentration: $\sum_i \pi_i \log \pi_i$

Spectral Radius: The largest eigenvalue in absolute value of the relevant propagation matrix

A second dimension is the distribution of nodes. For instance, concentration, $\text{NC} = \sum_i \pi_i \log \pi_i$, rises when a few large nodes dominate the total output of the network (Herskovic 2018). In such economies, shocks hitting those nodes have disproportionate aggregate consequences, the granularity hypothesis becomes particularly relevant, and resource allocation may be inefficient even if many links exist.

In the linear propagation benchmark above, shock amplification is governed by the largest eigenvalue (in absolute value) of the relevant propagation or coefficient matrix. In the SAR that matrix is $\rho\mathbf{W}$, and because $\mathbf{W}$ is row-normalized, the spectral radius of $\rho\mathbf{W}$ is $|\rho|$. More generally, when propagation instead runs through a structural coefficient matrix that is not row-normalized (such as the input-coefficient matrix $\boldsymbol{\Omega}$) the largest eigenvalue $\chi_{\max}(\boldsymbol{\Omega})$ itself governs amplification: as $\chi_{\max}(\boldsymbol{\Omega})$ approaches one, higher-order paths decay more slowly. In nonlinear models, the same logic applies only locally after replacing the operator with the relevant Jacobian. We emphasize that a single eigenvalue is useful but does not summarize every network response. In particular, thresholds, defaults, fire sales, and complementarities can generate amplification that no global eigenvalue captures (Baqaee & Farhi 2019).

2.3.3. Limitations of Reduced-Form Modeling. While spatial autoregressions are useful for estimating network effects, this approach has important limitations.

First, the network $\mathbf{W}$ is taken as given and typically treated as fixed. In reality, links evolve as firms form or sever relationships, and banks rewire their exposures in response to risks. The reduced-form approach cannot account for how the network structure may change over time. For econometric treatments of network formation, which the reduced-form approach above does not address, see de Paula (2020) and Graham (2020).

Second, the linear propagation assumption with a constant ρ is restrictive. Its magnitude is arbitrary and not disciplined by economic primitives. In production settings, for example, ρ should equal the capital share of output times returns to scale (Herskovic 2018). More generally, propagation intensity can be state-dependent: spillovers may amplify nonlinearly during crises. For heterogeneous-coefficient SAR models, which are useful when propagation intensities differ across nodes, see Aquaro, Bailey & Pesaran (2021).

Third, estimation results can suffer from identification challenges familiar from the reflection and peer-effects literatures (Manski 1993, Bramoullé, Djebbari & Fortin 2009, Blume et al. 2015). If $\mathbf{W}$ is correlated with unobserved fundamentals, or if links form in anticipation of shocks, regressions may pick up spurious "network effects" driven by common shocks, endogenous matching, or omitted variables. Empirical work addresses this in different ways, including high-frequency settings where shocks are better identified, lagged or predetermined networks, instruments built from distant exogenous shocks, and designs that separately measure direct and indirect exposure (e.g., Khwaja & Mian 2008, Barrot & Sauvagnat 2016, Ozdagli & Weber 2026).

Because of these limitations, structural approaches such as equilibrium models of network formation and contagion are valuable complements. Some studies take the network $\mathbf{W}$ as given and focus on estimating or disciplining ρ and linking it to risk premia; others endogenize the network itself, treating $\mathbf{W}$ as the outcome of agents' policies. These extensions are discussed in the subsequent sections.

3. Systemic Risk and Policies

3.1. What is Systemic Risk?

Any economic network entails a fundamental trade-off: links generates private and social benefits, yet they also create channels for adverse spillovers. The upside of interconnections is that gains, innovations, or risk-bearing capacity can spread across the network. For example, an investor's valuable information may diffuse to others, or a bank can share liquidity with peers, improving stability in normal times. The downside, however, is that local problems can also spread: an adverse shock at one node can transmit through the links, creating cascades. This downside constitutes *systemic risk*: the risk that an initially localized shock escalates through network contagion into a broader disruption or financial instability, reducing welfare by destroying resources, distorting allocations, or impairing risk sharing.

Systemic risk is different from *systematic* risk, and we use the two concepts as an organizing structure. By systematic risk we refer to shocks that are (exogenously or endogenously) aggregate in nature, and consequently, embedded in the stochastic discount factor (see Sharpe 1964, Ross 1976). By contrast, by systemic risk we refer to cascading failures across many nodes, markets, or sectors, potentially system-wide, even in the absence of an aggregate shock (see Benoit et al. 2017, Jackson & Pernoud 2021). Put differently, systemic risk is about propagation, while systematic risk steps beyond into aggregation. We focus on systemic risk in this section, while turning to systematic risk in the next, showing how network topology shapes priced risk factors.

Propagation and systemic risk can be conceptually related to the network transmission coefficient ρ introduced in equation (1), conditional on $\mathbf{W}$. If ρ is unconditionally zero, connections carry no contagion and shocks remain localized. When $\rho > 0$, a shock to one node affects its neighbors (and neighbors' neighbors, etc.), potentially turning an idiosyncratic loss into a cascade. The literature on systemic risk empirically documents or theoretically endogenizes the degree and pattern of transmission across counterparties, which are time-varying and state-dependent in ways that linear reduced-form models cannot fully capture.

Existing surveys provide great details on this regard and on the broader literature of systemic risk (see Bisias et al. 2012, Glasserman & Young 2016, Benoit et al. 2017, Jackson & Pernoud 2021, Elliott & Golub 2022). Our contribution is complementary by taking a higher-level, *network-of-networks* perspective. First, we revisit the major benefits versus risks for each type of network in Section 2.1, distilling why their links exist and what vulnerabilities they create. Second, we consider how networks intersect with one another via the meta-network, as systemic risk often emerges from the interplay of multiple networks. This broader perspective clarifies policy trade-offs.

3.2. Benefits Versus Risks of Network Structures

This subsection synthesizes the literature, from a systemic risk perspective, on the benefits and costs of the different types of networks discussed in Section 2.1. While connections generate gains in normal times, they can also trigger cascades during periods of stress.

3.2.1. What are Network-Specific Tradeoffs?

Production networks. Production-based links allow specialization and efficient firm boundaries, by channeling knowledge and resources through both within-firm plant networks (Giroud & Mueller 2019, Giroud et al. 2024), and across-firm ties. Trade credit along supply chains provides financing and can buffer liquidity shocks (Petersen & Rajan 1997, Cuñat 2007, Burkart & Ellingsen 2004). The structure of this financing is not random; it follows a clear vertical pattern where more upstream firms consistently provide more net trade credit (Gofman & Wu 2022). This structure serves a dual role: it not only channels liquidity down the production chain but also aligns incentives by acting as a commitment device to mitigate moral hazard by suppliers (Kim & Shin 2012).

These benefits come with systemic costs. Distress and uncertainty at upstream suppliers can transmit to downstream customers (Barrot & Sauvagnat 2016, Grigoris & Segal 2026). Trade credit can also propagate shocks when financing is withdrawn or counterparties default along the chain (Boissay & Gropp 2013, Jacobson & von Schedvin 2015). Firms attempt to mitigate these risks by diversifying suppliers, holding inventories, or vertically integrating critical inputs (Williamson 1985, Antràs 2016).

Competition and common-ownership networks. Competition networks disseminate information and shape corporate behavior as firms learn from rivals' policies (Leary & Roberts 2014). However, this peer-driven imitation can synchronize leverage, potentially amplifying shocks when conditions deteriorate. Competitive pressure also tightens margins and raises financing costs, reducing cushions against adverse shocks (Valta 2012). Strategic interactions in distress can further transmit shocks across rivals (Chen et al. 2023). Pellegrino (2025) formalizes this viewpoint in a network oligopoly model, in which firms' markups are partly determined by a network-centrality component: firms that are more central in the competition network face stronger competitive pressure and transmit demand shocks more strongly through their links to rival firms.

Moreover, common ownership by institutional investors may soften product-market competition (Azar, Schmalz & Tecu 2018, Backus, Conlon & Sinkinson 2021). Common ownership can also alter managerial incentives in ways that make rivals' policies more similar (Antón et al. 2023).

Banking and OTC networks. In normal times, interbank connections help institutions insure idiosyncratic liquidity shocks, reallocating funds where needed and reducing redundant cash buffers (Allen & Gale 2000). Due to persistent relationships between market participants in OTC markets, they are effectively modeled as a trading network in which assets and risks are allocated from the initial seller towards the final buyer via a chain of trades facilitated by intermediaries (Gofman 2014). Interbank links and cooperative arrangements such as syndicated loans also diversify exposures and share monitoring costs (Dennis & Mullineaux 2000, Sufi 2007). Likewise, OTC dealer networks concentrate liquidity provision and risk-bearing in a few key intermediaries (Bech & Atalay 2010, Gofman 2017, Hollifield, Neklyudov & Spatt 2017, Li & Schürhoff 2019, Eisfeldt et al. 2023, Eisfeldt, Herskovic & Liu 2024, Sambalaibat 2025).[8] Relatedly, in securities lending markets, Chague et al. (2017) show that better-connected short-sellers face lower search costs and therefore pay lower loan fees.

However, financial links create contagion channels. A single default can trigger cascades of counterparty losses (Eisenberg & Noe 2001), and overlapping asset portfolios induce fire-sale feedback loops (Shleifer & Vishny 1992, Cifuentes, Ferrucci & Shin 2005, Glasserman & Young 2016). Following Lehman's collapse, bank credit supply contracted sharply as institutions hoarded liquidity (Ivashina & Scharfstein 2010). Network topology can enhance fragility: interbank markets often display a core–periphery structure, so shocks to core institutions propagate widely (Craig & von Peter 2014). Anticipated support for central nodes can induce moral hazard (Farhi & Tirole 2012, Erol 2019). OTC contracts create additional externalities that amplify fragility: banks hedge idiosyncratic exposures but neglect counterparty-risk spillovers, resulting in inefficient under-hedging and systemic vulnerability (Zawadowski 2013). Empirically, Brunetti et al. (2019) show that the U.S. interbank network's lending links contracted sharply during the 2008 crisis even as market-based (correlation) connections among banks strengthened, underscoring that distinct networks reveal different dimensions of systemic stress.

Funding and investor networks. Investor networks diffuse governance norms: venture capital syndicates pool expertise and improve startup success (Hochberg, Ljungqvist & Lu 2007), while large institutional investors can influence firms' governance practices through stewardship and shareholder interventions (Appel, Gormley & Keim 2016, Dimson, Karakaş & Li 2015).

Yet these benefits create fragility. Overlapping portfolios create fire-sale contagion: if large investors must liquidate assets, falling prices impose losses on others holding those securities (Manconi, Massa & Yasuda 2012). Moreover, common-ownership links among competing firms may soften product-market competition and synchronize corporate policies, creating correlated vulnerabilities (Azar, Schmalz & Tecu 2018, Backus, Conlon & Sinkinson 2021, Antón et al. 2023).

Informational networks. Information flows through investor and manager social ties,

[8]Related, using transaction-level data, Paddrik, Ramírez & McCormick (2021) document trading in the U.S. overnight triparty repo market (an OTC funding network exceeding $1 trillion in daily volume) showing how relationship structures and collateral characteristics shape intraday liquidity allocation and pricing.

and through news channels. These connections accelerate diffusion and reduce search or attention frictions, improving price discovery (Cai & Szeidl 2018, Ahern 2017, Ozsoylev et al. 2014).

Yet the same networks can also amplify volatility and misinformation contagion. Rapid diffusion of news through central nodes can trigger herding and synchronized trading disconnected from fundamentals (Ahern 2017, Ozsoylev et al. 2014). Moreover, when the structure of information flows is strategically opaque (Erol & Lee 2025), risks can remain hidden until suddenly revealed, producing cascades.

Director and executive networks. We treat director and executive networks as a form of information-and-governance layer rather than a direct balance-sheet contagion channel, since they do not create contractual payment obligations and therefore do not transmit an Eisenberg–Noe clearing cascade directly (Eisenberg & Noe 2001). Board interlocks and executive social ties give firms access to external resources, advice, and information, diffusing practices and enabling peer learning across firms (Fracassi 2017, Cai & Szeidl 2018), which can improve monitoring and reduce information frictions.

Additionally, CEO–director ties are associated with reduced monitoring and value-destroying decisions (Fracassi & Tate 2012). In Special Purpose Acquisition Companies (SPACs), directors serving on multiple boards may face conflicts of interest and allocate merger targets to the SPAC that offers them higher compensation, at the expense of other SPAC's investors (Gofman & Yao 2026). Their relevance to the systemic-risk theme is indirect: governance ties can align leverage, investment, payout, disclosure, or compensation policies across firms, creating correlated vulnerabilities when the aggregate state deteriorates.

3.2.2. What are the Meta-Network Tradeoffs?

Networks do not operate in isolation: production, funding, banking, social, and information networks interact with one another, forming an overarching meta-network. The interconnectedness of this meta-network has several benefits as outlined in Section 2.1, but also means that shocks can spill over from one network to another, enhancing systemic risk. Despite its importance, the meta-network perspective remains relatively underexplored in the literature, with a few exceptions (see, e.g., Aymanns, Georg & Golub (2023), Hsu et al. (2025)). Evidence of inter-network shock propagation appears in some studies, even if not explicitly framed as meta-network analysis.

The meta-network adds more than the insight that networks interact: it changes how a shock compounds. We illustrate this via a production–banking networks relation. Let $\mathbf{W}^P$ be an $N_P \times N_P$ weighting matrix of the production network, assuming N_P productive firms, where $\mathbf{W}^P(i,j)$ is the share of firm i's inputs sourced from firm j, so that a demand shock at i propagates upstream to its suppliers via row i of $\mathbf{W}^P$. Let $\mathbf{W}^B$ be an $N_B \times N_B$ weighting matrix of the inter-bank network, assuming N_B banks. Lastly, denote by $\mathbf{C}^{PB}_{N_P \times N_B}$ and $\mathbf{C}^{BP}_{N_B \times N_P}$ be *Network-Connecting* matrices: the first maps the spillover effects from firms to banks (e.g., normalized balance sheet effects), and the second the spillovers from banks to firms (e.g., credit lines). In general, $\mathbf{C}^{PB}$ need not be the transpose of $\mathbf{C}^{BP}$. The connecting matrices here transmit a fraction of the shock received, so in this example, propagation is continuous and marginal rather than a discrete default cascade.

In a meta-network analysis, a shock can leave one network, travel through another, and return transformed. To fix ideas, trace a single cross-network path. Assume that firm i is hit by an adverse unit-size demand shock, represented by the row vector $-e_i$.[9] Its direct suppliers become affected, captured by $-e_iW^P$. In turn, connected banks, holding loans to firms, reassess their exposure to firms and see their deployable capital erode proportionally to $-e_iW^PC^{PB}$. Thinner capital leads these banks to reduce loans, so the strain spreads from bank to bank, captured by $-e_iW^PC^{PB}W^B$. The affected banks then reduce lending to firms that never dealt with the original firm i, captured by $-e_iW^PC^{PB}W^BC^{BP}$. The credit-constrained firms in turn cut input purchases and investment, so the weakness propagates along supplier–customer links $-e_iW^PC^{PB}W^BC^{BP}W^P$. In particular, the adverse effect of a shock originating at firm i and ending at firm j from a single cross-network path is

$$-e_iW^PC^{PB}W^BC^{BP}W^Pe_j^T. \qquad 2.$$

Note that this effect may be non-zero even if $W^P(i,j) = 0$: firm j can look disconnected from the initial shock within the production network only, yet become exposed via the meta-network. In this single cross-network path example, the shock started as a demand shock and returned to firms as a funding-like shock.

Whether such paths amplify or dampen a shock is state-contingent, depending on the substitution between banking and funding networks. They amplify when the second network transmits distress in the same direction. In the production–banking loop, a real shock weakens borrowers' balance sheets and raises loan losses at exposed banks, cutting credit supply to other firms (Kiyotaki & Moore 1997, Federico, Hassan & Rappoport 2025). The credit-constrained firms in turn cut trade credit and input purchases, propagating the shock to customers and suppliers (Bigio & La'O 2020, Costello 2020, Huremović et al. 2026). A funding shock works similarly: forced liquidations by large investors trigger fire sales that depress asset prices, hitting other investors directly, banks through mark-to-market losses, and firms through a higher cost of capital (Adrian & Brunnermeier 2016). Paths dampen shocks, by contrast, when another network supplies a substitute source of liquidity, information, or risk-bearing capacity: bond funding replacing bank credit, trade credit replacing withdrawn loans, or unlevered ownership absorbing what would otherwise be a fire-sale (Allen & Gale 2000). The organizing principle is complementarity versus substitution, a distinction made by Denbee et al. (2021) within the interbank network but operating across networks.

This perspective also sharpens the empirical challenges. The challenge is not observing several networks, but identifying the network where the shock originates and the networks through which it travels. Production, lending, ownership, director, and information links are jointly endogenous, so a single-network regression suffers *omitted-network bias*, with one adjacency matrix's coefficient absorbing exposure that runs through an excluded network. Origin is also ambiguous: a production shock can look like a banking shock when lenders cut credit upon observing weak borrowers, and the reverse when credit-constrained suppliers cut deliveries.

The object of interest is not whether cross-network spillovers exist but how large a share of a shock's total effect travels through paths that leave one network and re-enter through another. Estimating that share credibly requires three ingredients. First, the shock must have a known network of origin: supplier disasters, plant accidents, or tariffs in production networks (Barrot & Sauvagnat 2016, Boehm, Flaaen & Pandalai-Nayar 2019), or

[9]For expositional purposes, we use row-vector notation in this subsection.

lender capital and liquidity shocks in banking networks (Khwaja & Mian 2008, Chodorow-Reich 2014). Second, exposures must be measured before the shock, so propagation is not contaminated by network rewiring. Third, a cross-network exclusion restriction must hold, with the production shock reaching banks only through their lending to exposed firms and the banking shock reaching production only through credit supply. This last assumption is the binding one, since any direct channel between the two networks would contaminate the estimated cross-network component.

A credible design would use at least two networks defined over a shared set of nodes and split the total response into the part that stays within a network and the part that crosses between them. The estimator that does this is a spatial-autoregressive (SAR) model from Section 2 on the stacked meta-network rather than on either network alone. In our production–banking example, collect firm and bank outcomes in $\mathbf{y} = (\mathbf{y}^P, \mathbf{y}^B)$ and let each node load on its neighbors across all four blocks,

$$\mathbf{y}_t = \mathbf{y}_t\,\mathbf{R} + \mathbf{X}_t\beta + \boldsymbol{\varepsilon}, \qquad \mathbf{R} = \begin{pmatrix} \rho_P\,\mathbf{W}^P & \rho_{PB}\,\mathbf{C}^{PB} \\ \rho_{BP}\,\mathbf{C}^{BP} & \rho_B\,\mathbf{W}^B \end{pmatrix}, \tag{3}$$

where ρ_P and ρ_B govern propagation within production and within banking, ρ_{PB} the crossing of firm distress onto bank balance sheets, and ρ_{BP} the crossing of bank conditions onto firms through credit supply. The reduced form $\mathbf{y} = (\boldsymbol{\mu}+\boldsymbol{\varepsilon})(\mathbf{I}-\mathbf{R})^{-1}$collects all walks through the meta-network, with the banking crossover $\mathbf{W}^P\mathbf{C}^{PB}\mathbf{W}^B\mathbf{C}^{BP}\mathbf{W}^P$ among them.

A single-coefficient SAR on the stacked weight matrix, $\mathbf{y} = \rho\,\mathbf{y}\,\mathbf{R} + \cdots$ with one ρ and no block structure, recovers only total propagation and cannot tell a within-network path from a crossing. With the four coefficients the cross-network component is read off by comparing the full reduced form against the counterfactual that switches the crossings off, $\rho_{PB} = \rho_{BP} = 0$, which makes $\mathbf{R}$ block-diagonal and the two networks independent, so a production shock never reaches banks. The share of that shock's total response carried by the off-diagonal blocks is the cross-network multiplier.

The cross-network multiplier is read off the fitted block structure of $\mathbf{R}$. A complementary check looks instead at the timing of the response. Trace it period by period and ask whether it arrives in the order the propagation example predicts, first among directly exposed nodes in the originating network, then in the linked network, and only later back among the originating network's other nodes. Costello (2020) is the closest precedent, tracing a bank-lending shock through suppliers' trade credit onto downstream customers, though it follows one direction rather than estimating the full cross-network share.

The most promising network pairs share nodes, collateral, or attention: banking–production (the same firm borrows and supplies), funding–production (investor flows, common ownership, fire sales), funding–banking (overlapping securities and collateral), production–information (operational shocks become price-relevant only when investors recognize them), director–information (governance ties transmit policy templates and monitoring), and household–banking (dispersed depositors coordinate withdrawals). These pairs connect real cash flows, financing constraints, information, and risk-bearing capacity, which is what makes them likely sources of cross-network multipliers.

3.3. Policy Interventions

The frictions in Sections 3.2.1 and 3.2.2 raise a practical question: how can policy tilt networks toward resilience without eroding their benefits? One lens is through the life-cycle of systemic risk—*ex ante* (rules that shape links), *during* crises (targeted containment), and *after* crises (rewiring toward healthier topologies)—with each stage balancing efficiency, stability, and moral hazard.[10]

Importantly, privately formed connections are rarely socially optimal: private bailouts are not always credible (Leitner 2005), agents neglect contagion externalities when forming links (Elliott, Golub & Jackson 2014, Capponi, Du & Stiglitz 2024), expectations of rescue can foster correlated risk-taking (Acharya 2009, Farhi & Tirole 2012), opacity and asymmetric-information frictions in OTC markets sustain fragile structures (Di Maggio, Kermani & Song 2017, Jackson & Pernoud 2021), and activity can migrate outside the regulatory perimeter into lightly supervised "shadow" channels (Gennaioli, Shleifer & Vishny 2013). Consequently, the macroprudential task is to internalize these externalities across both intra- and inter-network links.

Ex ante. Policy tools set who can link to whom and at what scale. Gofman (2017) show that caps on counterparties lengthen intermediation chains and lower allocational efficiency, and that stability is non-monotone: modest connectivity reductions can dampen cascades, but enforcing a uniform (regular-degree) architecture can make the system less stable. Corbae & Gofman (2022) argue that antitrust leniency raises the cost of collusion, inducing banks to use long-term interbank loans as a commitment not to compete by restricting lending capacity. This raises borrowing costs and adds bilateral exposures, increasing network fragility. Cross-network channels amplify these effects as bank credit supply shocks spill into the real economy (Khwaja & Mian 2008, Chodorow-Reich 2014) and overlapping portfolios propagate fire-sale pressures (Manconi, Massa & Yasuda 2012).

During crises. Interventions should stop contagion at minimum cost. A network view highlights where support yields the greatest systemic benefit: rescuing a highly central node can stabilize more than aiding a larger but peripheral one (Acemoglu, Ozdaglar & Tahbaz-Salehi 2015). Tools such as DebtRank implement this targeting idea (Battiston et al. 2012). Authorities must weigh bail-outs, which stop runs but fuel moral hazard, against bail-ins, which preserve discipline but may spread stress if creditors are themselves central. There is usually a short window to act even with imperfect network maps (Upper & Worms 2004). This motivates the development of high-frequency systemic risk measures, such as those derived from real-time payment networks data (Chapman, Gofman & Jafri 2019).

After crises. As networks are rewired, the aim is to preserve economic function while avoiding new single points of failure. A prominent example is the post-2008 mandate, under Title VII of Dodd–Frank, to clear standardized OTC derivatives through a central counterparty, replacing bilateral webs of exposure with a hub-and-spoke architecture. This brings greater transparency and less scope for default cascades, but at a cost: it concentrates risk in critical hubs that must be robust, backed by conservative margins, recovery and resolution plans, and supervision (Duffie & Zhu 2011, Cont 2017, D'Erasmo, Erol & Ordoñez 2025). Other post-crisis measures add redundancy around critical nodes and improve the data and models used to map bilateral exposures, so that future interventions can be better targeted (Mistrulli 2011, Anand, Craig & Von Peter 2015).

[10]The network approach also highlights that regulators operate under uncertainty about the true pattern and strength of interconnections, which can limit the effectiveness of macroprudential tools. Ramírez (2019) models the planner's problem when the financial network is only partially known, showing that uncertainty about network structure constrains the scope for welfare-improving regulation.

Our meta-network approach highlights additional challenges faced by regulators. Regulators must evaluate how an intervention in one network propagates to other networks through linkages connecting production, banking, funding, information, governance, and regulatory bodies themselves.

4. Systematic Risk and Valuation

4.1. Endogenous Risk Factors

Consider innovations to a single-factor SDF,

$$M_{t+1} - E_t[M_{t+1}] = -\lambda\,\sigma\,\varepsilon_{t+1}, \qquad 4.$$

where ε_{t+1} is a single priced shock, σ is the quantity of risk, and λ is the risk price. When $\lambda > 0$, a positive realization of ε_{t+1} corresponds to a low-marginal-utility, or good state. Standard models posit that ε_{t+1} are aggregate shocks (e.g., to expected consumption growth or productivity; see Bansal & Yaron (2004), Croce (2014), Papanikolaou (2011)). The network view instead microfounds ε_{t+1} by showing how granular shocks propagate through links, such that the risk factors' definitions (including their risk prices and risk quantities) are determined by network topology.

4.1.1. When Does Idiosyncratic Risk Become Systematic?

In a well-diversified economy, firm-specific shocks should cancel, leaving aggregate consumption and returns unchanged. Classic production-based asset pricing models treat firm-level idiosyncratic shocks as diversifiable (e.g., Jermann 1998, Zhang 2005). In these frameworks, only aggregate shocks matter for asset prices.

This cancelation, however, relies on the law of large numbers, which can fail when firms are sufficiently heterogeneous in size or network position. Jovanovic (1987) argued that micro-level shocks can accumulate into macro fluctuations, and Bak et al. (1993) provided a complex-systems rationale for why such aggregation might be pervasive.

A network perspective formalizes this idea: when firms are interconnected, shocks no longer remain confined to the firm but can travel through input–output or financial linkages, changing the distribution of aggregate outcomes. If a firm or sector is sufficiently large or central, its "idiosyncratic" shocks affect many others and ultimately household consumption, making them systematic risks that investors cannot diversify.

Network models specify two ways this cancelation can fail. The first is strong linear propagation. In the SAR benchmark,

$$\mathbf{y} = (\mathbf{I} - \rho\mathbf{W})^{-1}(\mathbf{X}\beta + \boldsymbol{\varepsilon}),$$

and the multiplier series $\sum_{k\geq 0}(\rho\mathbf{W})^k$ converges if and only if $|\rho| < 1$ (see Section 2.3.2). When $|\rho|$ is well below one, the higher-order terms $\rho^k\mathbf{W}^k$ decay quickly and firm-level shocks remain mostly diversifiable. As positive ρ approaches one from below, these terms attenuate slowly, so a local shock travels through long chains and reaches many nodes.

The second mechanism is skewed aggregation, and it operates even when $|\rho|$ is well below one. Sufficiently uneven size or connectivity can concentrate influence in a few hub nodes and prevent the law of large numbers from applying. In production networks this influence is captured by Domar weights and higher-order input–output linkages. Shocks to high-weight or highly central nodes can scale up to macro shocks without near-unit SAR amplification (see, e.g., Gabaix 2011, Acemoglu et al. 2012).

Empirical evidence supports this view. Gabaix (2011) shows that shocks to the largest U.S. firms, that is, the "granular residual", explain roughly one-third of GDP fluctuations, because extreme skewness in the firm size distribution prevents full diversification. Barrot & Sauvagnat (2016) find that natural disasters hitting key suppliers reduce downstream and aggregate production, while Boehm, Flaaen & Pandalai-Nayar (2019) show that the 2011 Tōhoku earthquake in Japan propagated globally through supply chains. In short, idiosyncratic shocks become systematic when network structure prevents diversification, transforming local shocks into economy-wide events that command risk premia.

4.1.2. What Systematic Risk Factors Do Networks Create? In a multi-sector production economy, Herskovic (2018) show that two network-based factors enter the SDF alongside aggregate productivity: network sparsity and network concentration. Sparsity aggregates information from the rows of the input–output matrix (weighted entropies of input shares) and captures input specialization (see Section 2.3.2). Concentration aggregates equilibrium output shares across nodes (negative entropy over node sizes; see Section 2.3.2). The SDF falls with innovations to sparsity and rises with innovations to concentration. Intuitively, greater specialization boosts efficiency and consumption (good state, $\lambda > 0$), whereas the dominance of a few nodes creates inefficiencies and lowers consumption (bad state, $\lambda < 0$).

A complementary mechanism ties long-run risk to how strongly shocks propagate across links. In Ramírez (2024), the propensities of supplier–customer links to transmit shocks evolve slowly. These propensities define a propagation state: When higher, firm-level shocks travel farther downstream, making aggregate consumption growth more sensitive to micro shocks. Because the propagation state is persistent, its movements induce a low-frequency component in expected consumption growth: a network microfoundation of long-run risk. Moreover, an innovation that raises the propagation state is akin to a "contagion" shock, elevating transmission, and consequently, the conditional volatility of consumption growth. Thus, it carries a negative price of risk.[11]

Link durability itself can act as a priced factor. Grigoris, Hu & Segal (2023) model supplier–customer severance risk: if links break, suppliers incur customer search costs, which are systematically more severe in downturns. Suppliers can partially hedge this severance risk by extending trade credit to customers, as this lengthens the expected duration of existing relationships. Consequently, the aggregate amount of trade credit is a proxy for the economy-wide state of customer-search costs. Innovations to this proxy act as a "counterparty" (search-cost) risk factor with a negative price of risk, because rising search costs occur in high-marginal-utility states. In essence, this factor captures the average probability of link severance.

At the international level, trade networks generate global risk factors. Jiang & Richmond (2023) develop a multi-country model with segmented financial markets where trade-network linkages transmit local shocks across countries. This propagation compresses many idiosyncratic shocks into a few global components, summarized by trade network centrality: an export-share–weighted measure of how strongly a country's tradables enter others' consumption bundles. These components emerge as systematic factors in currency returns,

[11] Related, Buraschi & Tebaldi (2024) show in a financial-network setting that when distress propagates along interconnections and firm-specific shocks cease to diversify, equilibria feature non-diversifiable cascades ("financial pandemics") that can command a distinct network risk premium not spanned by standard aggregate factors.

so the topology of world trade endogenously delivers the factor structure of exchange rates.

While existing literature focused on how individual network topologies shape systematic risks, the asset-pricing implications of interacting or meta-networks remain largely unexplored, even as their systemic-risk side is developed in Section 3.2.2. The systematic-risk analogue of the cross-network multiplier is a cross-network state variable in the SDF: a banking shock should be priced differently when production networks are concentrated or trade credit is fragile. Spillovers across domains may therefore generate priced risks beyond those captured by isolated networks. We return to this point in Section 6.

4.1.3. How Does the Network Structure Affect the Quantity of Risk? The quantity of systematic risk refers to the volatility of aggregate fluctuations and hence, of the SDF (σ in equation (4)). With many independent, unlinked firms, micro shocks diversify away and do not affect this quantity. Two departures prevent this. First, granularity (as in Gabaix (2011)) sets a floor for σ when a few firms are very large. Second, network topology with propagation can turn firm-specific shocks into aggregate fluctuations even when firm sizes are similar. As shocks travel through supplier–customer links, they become correlated, failing to diversify and raising aggregate volatility.

Acemoglu et al. (2012) formalize this idea. Aggregate output is a sum of sectoral shocks weighted by each sector's Domar weight (see Section 2.3.1). Aggregate variance is thus the sum of squared Domar weights times shock variances, a quadratic form shaped by the input–output matrix. This suggests that diversification hinges on second-order connectivity: a sector matters not only because it sells to many customers, but because its customers themselves are pivotal suppliers. Moreover, the cross-sectional distribution of these second-order influences has a heavy tail, suggesting that aggregate volatility decays with the number of sectors much slower than the textbook $1/\sqrt{n}$, closer to $n^{-0.15}$. Two economies with the same number of sectors can therefore exhibit very different macro volatility: hub-like structures amplify the quantity of systematic risk.

The bridge to asset pricing comes from an anomaly: the common idiosyncratic volatility (CIV). Herskovic et al. (2016) show that a single factor explains about one-third of the time-variation in firms' idiosyncratic risks. In representative-agent models, this is puzzling, as idiosyncratic risk is uncorrelated between firms. The network view resolves the puzzle in the spirit of Acemoglu et al. (2012): much of what looks idiosyncratic is actually endogenous volatility, correlated across firms because shared suppliers and customers propagate shocks. Herskovic et al. (2020) formalize this. In a production network, a firm's volatility rises with the concentration of its customer base ("out-Herfindahl"). Economy-wide shifts in this concentration move firm-level volatilities together, giving rise to CIV.[12]

Network topology can also amplify the quantity of systematic risk by thickening the tails of aggregate outcomes. Acemoglu, Ozdaglar & Tahbaz-Salehi (2017) distinguish volatility from tail risk: the former depends on the dispersion of Domar weights, while the latter on dominance (how large a node's weight is relative to others). With sufficiently dominant sectors, even light-tailed micro shocks produce large aggregate downturns, where many sectors fall together.

A similar amplification appears in financial intermediation. Eisfeldt et al. (2023) estimate a structural model of CDS trading and show that core-periphery dealer networks

[12] Recently, Chen (2025) studies idiosyncratic volatility spillovers in production networks, which also give rise to economy-wide volatility factors.

distort risk sharing and elevate tail risk. Because protection selling is concentrated in a few core dealers, the failure of a dominant one can raise CDS spreads by up to 24%, whereas a complete network structure would mute this effect. The lesson mirrors production networks: concentrated and incomplete network topologies amplify market-wide risk and generate volatility spikes when key hubs are hit.

4.2. Endogenous Risk Exposures

Beyond the price of risk, λ, and the quantity of risk, σ, another determinant of firm-level risk premium, $\mathbb{E}[R_i^e]$, is risk exposure or the sensitivity of valuations to priced shocks, β_i:

$$\mathbb{E}[R_i^e] = \beta_i \lambda \sigma^2. \qquad 5.$$

Firms differ widely in their exposures to systematic risks such as market returns, productivity, or policy shocks. This raises the question of why some firms load more heavily on aggregate shocks than others. Network research microfounds exposures using the structure of linkages. Formally, β (in the notation of equations 1. and 5.) becomes a function of the adjacency matrix $\mathbf{W}$.

4.2.1. How Does a Node's Position Determine its Risk Exposure? A firm's network position: whether central or peripheral, upstream or downstream, bridging clusters or isolated, shapes how sensitive its value is to systematic shocks. This extends the standard logic of production-based asset pricing, where firms' policies and investment choices endogenize β. In networks models, exposures arise not only from a firm's own policies but also from its connectivity to others. Broadly, more strategically positioned firms exhibit cash flows that comove more strongly with aggregate conditions.

One classic result is that centrality drives systematic risk exposures, as shown by Ahern (2013). As discussed in Section 4.1.1, sectoral shocks can be a source of systematic risk when the network structure is highly asymmetric. Intuitively, central industries, like automakers, are more exposed to such shocks because disturbances from anywhere in the network are more likely to reach them or be transmitted through them. Peripheral sectors, like farming, are largely bypassed, so their cash flows remain more idiosyncratic. Empirically, industries with higher eigenvector centrality exhibit higher market betas, stronger covariation with aggregate consumption growth, and higher average returns. Similarly, Buraschi & Porchia (2012) find that more central firms have lower price–dividend ratios.

Branger et al. (2021) formalize and refine this logic in an equilibrium model with a directed network and mutually exciting jumps: a negative cash flow shock to firm j can raise the likelihood of future negative shocks to connected firm i. They decompose i's exposure to firm-j shocks into a "receiving" and a "hedging" component. The receiving term is negative, reflecting a spillover effect. The hedging term is positive since a shock to j can make i relatively more attractive as a hedge against propagation risk. This hedging force is stronger when j has high spreading capacity (i.e., its shocks propagate broadly). Central nodes have high receiving and spreading capacity but weaker hedging ability, yielding a centrality premium consistent with Ahern (2013).

A firm's distance to final consumers along supply chains can also endogenize its risk exposure (see Gofman, Segal & Wu 2020): the more upstream a firm is, the higher its beta. Aggregate productivity shocks have two countervailing effects: a demand effect that raises growth-option value, and a supply effect in which more productive suppliers devalue their customers' assets-in-place by lowering the replacement cost of installed capital. This channel where upstream innovation decreases downstream valuation is termed "vertical creative destruction." It propagates downstream, so firms closest to consumers experience the largest offset between supply and demand effects, making their productivity exposures the lowest. Empirically, expected returns and risk exposures increase monotonically with proximity to the top of the supply chains.

Those studies show how a firm's network position shapes its exposure to supply-side shocks. Such shocks generally propagate downstream, as in "vertical creative destruction." By contrast, demand-side shocks such as monetary-policy surprises propagate upstream from customers to suppliers, amplifying exposures in the opposite direction.

A prominent example pertains to monetary policy. Within the U.S., Ozdagli & Weber (2026) estimate a spatial regression akin to (1), in which the impact of policy shocks on stock returns can propagate upstream via the input–output matrix. Sector i's exposure can be written as $\left[(\mathbf{I}-\rho\mathbf{W}^\top)^{-1}\boldsymbol{\beta}\right]_i$, where $\mathbf{W}$ is the row-normalized input-share matrix, so $\mathbf{W}^\top$ carries demand shocks from customers back to suppliers, $\boldsymbol{\beta}$ is the vector of direct policy sensitivities, and the multiplier$(\mathbf{I}-\rho\mathbf{W}^\top)^{-1}$ captures indirect upstream amplification. In the data, the indirect component explains much of the total response, with upstream firms showing stronger network-driven exposure. Internationally, Di Giovanni & Hale (2022) apply the same logic to the global input–output network. Foreign equity responses to U.S. monetary shocks are mostly driven by network effects, via production links to the U.S.

More generally, international positions shape exposures to global shocks and currency risk. Richmond (2019), for example, shows that countries central in the global trade network have currencies that appreciate in bad times–because their consumption growth is more exposed to global shocks–and therefore earn lower average currency premia and interest rates. Peripheral countries, by contrast, are less connected to global risk and their currencies require higher premia. Thus, central currencies act as hedges.

4.2.2. How Do Edge Properties Affect Nodes' Risk Exposures? Not only who a firm is connected to, but how each link behaves, shapes exposure to priced shocks. The adjacency matrix $\mathbf{W}_t$ embeds time-varying edge states: transmission propensities, survival probabilities, and bargaining weights. As these states change, firms' betas also evolve.

Ramírez (2024), for example, considers edges' shock-transmission propensity as a time-varying primitive that moves W_t. Links' propensity to transmit shocks fluctuates systematically over time, creating a priced "contagion" shock. A firm's exposure to this risk depends on the mix and direction of its edges. In particular, firms that rely on a few suppliers connected by high-propensity ties are most exposed. Interestingly, accounting for time-variation in links' shock-transmission propensities reverses the usual centrality premium. As firms become more peripheral they rely more heavily on their suppliers, causing them to feature a high contagion-risk beta and a high risk premium.[13]

Links' duration is another dynamic property shaping exposures. Grigoris, Hu & Segal (2023) show that when links sever, suppliers bear the costs of finding new customers. These costs vary systematically, creating a new source of risk. Suppliers with short-duration links earn about 1% per month higher returns than those with long-duration links, reflecting

[13]To reconcile this outcome with Ahern (2013), Ramírez (2024) stresses that industry-level aggregation masks within-industry heterogeneity in shock-transmission propensities and directional reliance, which are the true drivers of firm-level contagion exposure.

greater exposure of the former to this risk. Firms can, however, actively manage their exposure through trade credit. By extending credit to valuable customers, suppliers insure the edge itself. Empirically, higher trade credit forecasts longer-lasting links and lower exposures to systematic customer-search costs.

A third edge property is bargaining power between trading partners. Bustamante (2018) show that surplus along a supply-chain link is split through vertical bargaining between a supplier and a customer. The firm with greater power extracts a larger share of the pair's continuation value, but in doing so absorbs more of the partner's systematic risk. Risk exposure thus shifts endogenously with bargaining power. Empirically, when customers have greater continuation value (lower book-to-market), they earn higher expected returns, consistent with them absorbing more risk through bargaining.

4.3. Price Efficiency

4.3.1. How Does Propagation Affect Valuations in Inefficient Markets? Network connections can generate temporary inefficiencies when information diffuses gradually through links. Suppose firm A supplies to firm B. If A receives bad news it could eventually hurt B, yet B's investors may not immediately incorporate it to the price. In efficient markets, arbitrageurs would react at once; in reality, limited attention and frictions delay the correction, so network links create predictable return patterns.

Evidence along vertical customer–supplier links is canonical in this regard. When a customer is shocked, its suppliers' valuations adjust with a lag, even though SFAS-131 requires public disclosure of such links. Customers' returns also predict suppliers' future profits, reinforcing that investors neglect readily available cross-firm information. Cohen & Frazzini (2008) build a "customer momentum" strategy: long (short) firms whose customers had high (low) returns last month, that earns abnormal returns of over 150 basis points per month. These profits stem from delayed incorporation of partner news, not exposure to systematic risk. Related, Aobdia, Caskey & Ozel (2014) show that industries predict the combined returns of their suppliers and customers, and this effect is stronger when the source industry is more central.

Market segmentation amplifies these effects. Using input–output connections, Menzly & Ozbas (2010) show that returns in supplier–customer industries cross-predict each other, with lagged shocks in one sector forecasting returns in the other. Cross-predictability is strongest where information intermediation is thin (low analyst coverage and sparse institutional ownership), and disappears where it is rich, pointing to gradual diffusion. Institutions also trade consistently with market specialization: they adjust holdings in a stock simultaneously with adjusting holdings in its connected suppliers and customers.

Predictability in production networks can persist even longer via "echoes." Sectoral shocks can travel through input–output loops and feed back to their origin, generating an intermediate-horizon echo in industry momentum profits, especially over the past 7–12 month horizon (Sharifkhani & Simutin 2021). Echo profits are largest when analyst co-coverage along the loop is low, exactly where diffusion frictions should bind most.

Delayed price propagation is not only vertical. A "competition network" links industries horizontally when they share multi-industry leaders. Dou & Wu (2023) show that focal industries comove with peers and underreact to their news. Sorting on peers' lagged returns yields large return spreads, stronger when attention is scarcer: lower analyst coverage or institutional ownership.[14]

4.3.2. Can Network Structures Improve Price Efficiency?

Certain network structures may improve price efficiency, when they provide clear, overlapping pathways for informed signals to propagate. In contrast, they impair efficiency when opacity and complexity dominate.

Density in "information networks" accelerates price discovery by channeling relevant signals to price-setting traders (see Ali & Hirshleifer (2020)). A notable case is shared analyst coverage: when two firms are followed by the same analysts, shocks to one firm are more quickly incorporated into its peer's valuation. This shared coverage effect is strong enough to subsume customer–supplier momentum, showing how analyst networks can speed the transmission of cross-firm news. While such connectivity speeds information transmission, inefficiencies still persist since analysts' forecasts adjust sluggishly to news from co-covered peers. Network complexity worsens the problem: when a firm is central in this information network, peer news diffuses into its valuation more slowly.

Investor trading networks provide another conduit of information. Ozsoylev et al. (2014) construct a network linking investors by similarity in their trading behavior. This approach produces a graph of who tends to trade with whom, and consequently, which investors are more central. Information about fundamentals does not reach all participants simultaneously: it flows first to central investors, who then trade in ways that gradually transmit the news into prices.

The topology of investor networks matters for efficiency. In a noisy rational-expectations model, Walden (2019) shows that more central networks, where information diffuses more effectively, or less irregular networks, where connectivity is balanced across nodes, promote price efficiency by speeding up the absorption of dispersed private information. By contrast, in less central networks prices take longer to incorporate signals, while in irregular networks volatility is more persistent because news moves quickly in some areas but lags in others.

Connectivity can also have adverse effects when investors see only part of the network. In Schneemeier (2018), each trader observes the prices of immediate neighbors but is uncertain about how those neighbors are linked to others. As a result, a neighbor's price move may be interpreted as fundamental news even when it simply reflects a reaction transmitted through hidden connections further away. Because of this opacity, shocks propagate in a distorted way: even distant shocks can be misattributed as relevant, slowing down the incorporation of true information.

5. Network Formation and Fragility

5.1. How Do Financial Networks Form?

Economic and financial networks evolve as firms, banks, intermediaries, and households make choices. Households decide which products to buy and where to borrow, firms select suppliers and may target specific customers, banks form relationships through interbank lending, and investors in over-the-counter markets choose their trading counterparties. The

[14] Cross-predictability exists along other forms of inter-firm connectivity including product market links (Schlag & Zeng 2019), strategic alliances links (Cao, Chordia & Lin 2016), trade credit links (Albuquerque, Ramadorai & Watugala 2015), information links (Cohen & Lou 2012, Burt & Hrdlicka 2021, Huang et al. 2022), technological links (Lee et al. 2019), geographical links (Parsons, Sabbatucci & Titman 2020), and labor market links (Bae et al. 2022).

resulting network structures emerge from the aggregation of these decentralized decisions. Network formation itself reflects agents' incentives (e.g., risk diversification, access to information or clientele) as well as their constraints (e.g., regulatory restrictions).[15]

In finance, a common tradeoff in network formation models is between risk sharing and contagion. In interbank markets, for example, connections allow banks to insure one another against liquidity shocks as banks themselves do not have to hold large idle buffers if they can borrow from other banks. This incentive leads to the formation of lending links in a way that can be socially optimal up to a point (Allen & Gale 2000).[16] However, beyond that point, a densely connected network may amplify contagion, as discussed in Section 3.

Do banks form too few or too many links relative to the social optimum? Babus (2016), Farboodi, Jarosch & Shimer (2023), and Elliott, Georg & Hazell (2021) proposed models where banks endogenously choose links. Individual banks may not internalize the systemic risk their links create, leading to externalities and networks that are denser and more interconnected than are socially ideal. Conversely, under some conditions, such as high counterparty risk, banks might avoid connections yielding a network too sparse with less mutual insurance. These formation incentives also depend on how liquidity interacts across counterparties: Denbee et al. (2021) show that complementarity (substitution) in reserve holdings makes the network amplify (absorb) shocks.

In production networks, firms form supplier relationships, taking into account cost, quality, and reliability. A firm could single-source a critical input for efficiency (scale economies or better coordination) or multi-source for resilience (supplier diversification). These firm-level decisions shape the aggregate network structure. Models like Elliott, Golub & Leduc (2022) explore how comparative advantage and contract frictions result in certain network architectures (e.g., dominant "star" suppliers). Frameworks such as Oberfield (2018) provide a theoretical foundation for why particular hub-and-spoke structures emerge in input–output networks, while more recent work by Kopytov et al. (2024) examines how uncertainty about supply disruptions influences the density and redundancy of links that firms form. Production networks also change through waves of mergers and acquisitions. Ahern & Harford (2014) show these waves propagate through existing supplier-customer links.

Social and informational networks, such as venture capital syndication, form for reasons like reputation and information flow. A venture capitalist might co-invest with certain others to pool expertise or to gain future deal flow, building a network that maximizes their access to opportunities (Hochberg, Ljungqvist & Lu 2007). In the context of information acquisition, Herskovic & Ramos (2020) develop an endogenous network formation model in which agents form links to learn from peers, showing that strategic complementarities in information acquisitions can lead to hierarchical network structures as an equilibrium

[15] Seminal contributions by Jackson & Wolinsky (1996) and Bala & Goyal (2000) provide different mechanisms for link formation. Subsequent work on endogenous network formation includes Borgatti & Everett (2000), Calvó-Armengol & Zenou (2004), Goyal & Vega-Redondo (2005), Hojman & Szeidl (2008), and König, Tessone & Zenou (2014). For reviews of the literature, see Bloch & Jackson (2006), Jackson (2010), and Hellmann & Staudigl (2014).

[16] For foundational models of over-the-counter trading and intermediation, see Duffie, Gârleanu & Pedersen (2005) and Atkeson, Eisfeldt & Weill (2015). Malamud & Rostek (2017) develop a general-equilibrium model of decentralized exchange in which decentralization always increases price impact, yet fragmentation can still raise welfare relative to a centralized market by improving risk sharing among heterogeneous traders.

outcome. Similarly, in OTC markets, Chang & Zhang (2015) and Wang (2016) show that when traders endogenously form connections, core–periphery trading networks emerge in equilibrium.

5.2. Why Do Nodes Fail?

A failure of a node in a financial network may originate from two sources: (i) internal, as a result of an intrinsic weakness of the node, or (ii) external, as a result of knock-on effects like contagion from connected nodes. In practice, these often coincide and interact: A bank or a financial intermediary may be hit by an adverse shock, but whether it causes a failure depends on the network. If the failing node has many counterparties, its distress can either spread to others, or be circumvented through connections that provide insurance.

Both types of node failure have been observed empirically. In 2008, Lehman Brothers failed due to losses on mortgage assets (an intrinsic shock), but its collapse was especially disruptive because Lehman was highly interconnected through derivative contracts and repurchase agreements. The sudden exit of such a central node sent stress through multiple channels as other banks lost a counterparty.

Theoretical models of cascades formalize when one failure triggers others. The seminal study of Eisenberg & Noe (2001) develops a clearing-payment framework for interlinked balance sheets. Defaults depend on both the pattern of liabilities (who owes whom) and the size of the shock relative to buffers. If a firm's losses exceed its capital, it fails and cannot fully pay creditors, which may push those creditors into default if the unpaid amounts are large relative to their own capital. This chain reaction is more likely in networks where obligations are concentrated. Similarly, Allen & Gale (2000) illustrate that a ring network of banks can transmit a localized shock all the way around the circle if each bank is heavily reliant on payments from its neighbor, whereas a more fully connected network allows risk-sharing that can absorb the shock. These models highlight that the structure of the network sets the stage for whether a node's failure is isolated or cascades system-wide.

Different network domains provide empirical illustrations of these mechanisms. In production networks, failures propagate through supplier–customer relationships. A shock to a key supplier can cascade downstream by sharply curtailing customers' output and market value, as limited substitutability of inputs turns local distress into broader supply-chain distress (see evidence in Barrot & Sauvagnat (2016)).

Finally, in OTC networks, the network structure determines how severe a failure of a single node (individual dealer) will be. Eisfeldt et al. (2023) develop a model of OTC trading in credit default swaps, featuring a core–periphery market where a handful of dealers dominate. Because dealers are heterogeneous in size and in the extent of risk-sharing, the exit of a single core dealer can raise CDS spreads by up to 24%. What makes a dealer systemically important is the combination of being highly interconnected and being a large insurance provider.

6. Future Directions and Hypotheses

As data availability and computational tools improve, our ability to analyze complex networks should increase. Below, we propose several directions for future research, including specific hypotheses on how the landscape of networks in finance could evolve with recent macroeconomic trends.

1. Network-to-Network Spillovers (the "Meta-Network"). As explained in Section 3.2.2, existing research typically restricts attention to one network type: production, banking, funding, information, or social. A promising avenue is to study how a shock that decays within one network is amplified when it crosses into another. Quantifying such spillovers means estimating the cross-network multiplier introduced earlier, that is, how much of a shock's total effect travels through paths that leave the originating network. This bears potential to explain excess correlation and volatility puzzles and uncover hidden fragility.

2. Networks with Slowly-Decaying Stock Variables and High-Performance Computing. Existing network models typically feature transitory *flows* of intermediate inputs across nodes. Studying network models with persistent *stocks* of existing goods is computationally challenging (NP-hard), becoming more feasible with increased computational power (e.g., quantum computing). Under supply-chain disruptions, firms may transition from "just-in-time" production to holding stocks of inputs as buffers, making this modeling choice increasingly relevant. Such models could alter how shocks propagate. For example, in traditional models, a negative productivity shock to some node i does not propagate upstream: the negative quantity effect on how much i produces cancels out by its higher output price. Yet if other firms hold an existing stock of goods produced by i, scarcity may not bind, and the negative shock might not lead to a sharp price appreciation. This allows the quantity effect on i to propagate upstream.

In relation to asset prices, holding a stock of inputs may raise nodes' direct exposure to systematic shocks, as stock management involves frictions, but may lower indirect network effects and systemic risk, since holding stock is a buffer against neighbors' downside risk. Moreover, as stocks of intermediate inputs help resolve the profitability premium jointly with the value premium (Kogan, Li & Zhang 2023), such network models could help microfound cross-sectional asset-pricing puzzles.

3. Networks as Identification Tools. Granular network data can turn distant shocks into relevant instruments for causal identification (e.g., Schubert 2021). One idea is a *directed network shift–share* instrument built from remote exogenous node shocks. Let $\varepsilon_{jt}^{\text{exo}}$ capture shocks that are orthogonal to firm i's fundamentals (e.g., natural disasters, plant accidents). Define $Z_{it}^{(k)} = \sum_{j \neq i} W_{ij}^{(k)} \, \varepsilon_{jt}^{\text{exo}}$, where $W_{ij}^{(k)}$ aggregates k-step upstream or downstream paths from i to j. $Z_{it}^{(k)}$ could instrument shocks affecting the valuation of i.

4. The Rise of AI, the Labor Share, and Network Effects. The impact of AI on labor-input usage and firm value is ambiguous (Eisfeldt, Schubert & Zhang 2023). On the one hand, AI-driven displacement of low-skilled labor and automation could further boost the secular decline in the labor share of income (see Karabarbounis & Neiman (2014)) and intensify reliance on capital inputs. This could strengthen network effects on policies and prices (in production setups, the decay rate of shock propagation equals the capital share of output times total returns to scale, see Herskovic (2018). On the other hand, AI may complement high-skilled labor by enhancing human capital. Since human capital is not transmitted along supply chains, this could weaken network pricing effects.

5. Big Data, Network Visibility, and Price Efficiency. Advances in big data will enable real-time analysis of financial networks. Enhanced network visibility could accelerate shock propagation into asset prices, improving market efficiency (as in Ali & Hirshleifer (2020)). This would reduce network-based return predictability driven by inefficiencies (as in Section 4.3.1). Conversely, reliance on the same public signals, along with opaque AI models, could result in noise contagion within investors' networks and lower price efficiency (similar to Schneemeier (2018)).

6. Supply-Chain Disruptions and Interest Rates. Global disruptions (trade wars, geopolitics) are likely to encourage firms to shorten supply chains and diversify their suppliers and customers, resulting in a denser network. This could lower specialization and network sparsity, resulting in lower expected consumption growth (as in Herskovic (2018)). This could contribute to the secular decline in interest rates. Simultaneously, a denser network could generate greater diversification of idiosyncratic shocks, reducing volatility, which would put upward pressure on interest rates.

7. Deglobalization and Network-Based Currency Risk. Deglobalization and reshoring can reduce the intensity of international production links, weakening global transmissions and lowering exposure to global shocks. Simultaneously, tariffs may foster regionalization of tightly connected countries within separate clusters. This can create common regional components in countries' consumption, raising dispersion of interest rates and currency premia within clusters, while reducing dispersion across them.

8. ESG and Sustainability-Based Networks. Investors increasingly base choices on firms' ESG practices. This shift implies: (i) ESG scores may become network-based, reflecting both a firm's operations and those of its suppliers; (ii) a new type of connectivity could arise, where two firms are linked if their operations contaminate the same local "environment" (similar location or labor-market segment) creating new paths for propagation; and (iii) production networks may become more segmented (brown versus green clusters), restricting economy-wide propagation. However, such segmentation could lengthen supply chains (e.g., if there is no direct green substitute for a brown supplier) and increase in-degree concentration, resulting in longer propagation paths and higher return volatility.

9. The Rise of Intangible Assets and Information Networks. A growing literature emphasizes the unique features of intangible capital for production and valuation.[17] The prominence of intangibles could alter how firms form connections. First, since intangible capital is not transmitted through supply chains, it could weaken the role of production networks while elevating the importance of information networks in generating comovement between firms' returns and policies. Second, because intangible capital is non-pledgeable (see Crouzet et al. (2022)), it could contribute to a decline in collateral-based lending, making financial networks more susceptible to cascading defaults, unless lower pledgeability would induce institutions to proactively form more diversified financial links.

10. Cryptonetworks and Decentralized Finance. Blockchain-based cryptonetworks are likely to reshape financial intermediation networks. Greater decentralization could alter network structures by reducing reliance on intermediaries, potentially decreasing systemic fragility. However, increased opacity and regulatory oversight may heighten node-specific risks and volatility.

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[17] See, e.g., Eisfeldt & Papanikolaou (2013, 2014), Eisfeldt, Kim & Papanikolaou (2022).

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