Mechanisms of Contagion in Financial Networks*

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Abstract

I develop a multi-sector core–periphery model of the banking system with correlated portfolios between counterparties and study how a sector-specific shock propagates through bilateral exposures and common asset holdings. I use this to show how the relative importance of interbank and fire-sale contagion depends on the size of the shock and characteristics of the financial network and markets. I first derive explicit thresholds at which different groups of banks default as the shock grows and decompose systemic losses at each threshold into interbank and fire-sale components. I then calibrate the model in a simple multi-sector example and simulate the response to shocks of increasing size, showing that small shocks are amplified mainly through interbank linkages, while large shocks are amplified mainly through fire-sale spillovers once core institutions are affected. Finally, I perform comparative statics that vary key features of the system—such as network structure, portfolio concentration, and market depth—and map them into the interbank share of contagion at each default threshold.

Keywords: Financial contagion; interbank networks; fire-sale externalities; core–periphery structure; correlated portfolios; systemic risk

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1 Introduction

Financial crises have repeatedly shown that shocks to a small set of institutions can spread widely throughout the financial system. The Global Financial Crisis began with mortgage-related losses at a handful of large banks but ultimately led to severe stress across a broad range of intermediaries and asset classes. Similar dynamics appeared in the 2023 regional banking crisis, where the failures of Silicon Valley Bank and Signature Bank raised concerns about wider instability in the banking sector (Acharya et al., 2023; Choi et al., 2023).

This vulnerability reflects the interconnectedness of modern financial systems, whether through direct lending in the interbank market, or overlapping portfolios of traded assets. As these connections have grown denser over recent decades, they have created two distinct channels through which shocks can propagate. Interbank contagion occurs when defaults cascade along chains of bilateral obligations, imposing counterparty losses on creditors (see, for example, Allen and Gale, 2000; Eisenberg and Noe, 2001; Elliott et al., 2014). Fire-sale contagion occurs when distressed institutions liquidate assets to meet obligations, driving down prices and generating mark-to-market losses for all holders of similar securities (see Cifuentes et al., 2005; Greenwood et al., 2015). A central question for understanding systemic risk is: which mechanism is more important for amplifying shocks, and how does this vary with shock size and network characteristics?

Recent work by Mikropoulou and Vouldis (2025) uses supervisory data on large euro area banks to study contagion in the financial network. They distinguish "direct" contagion through interbank liquidity hoarding from "indirect" contagion through overlapping portfolios and fire sales, and study the system's response to liquidity and asset-price shocks. Their key finding is that as shocks grow, indirect contagion increases much more sharply than direct contagion. For small shocks, losses are dominated by counterparty exposures, but beyond certain thresholds, additional losses are driven mainly by price-mediated spillovers. While this provides a clear empirical pattern, there is no stylised theoretical model that explains why the dominant channel of contagion should vary with shock size, or how this variation depends on network structure and balance-sheet composition.

In this paper, I develop a model of contagion in a core–periphery banking system that combines the cascade framework of Elliott et al. (2014) with an exponential fire-sale price impact mechanism from Gai and Kapadia (2010). Banks hold two classes of assets: interbank claims on other banks and risky "outside" assets backed by cash flows from different sectors of the real economy. Small "periphery" banks have more concentrated home-sector portfolios and fewer counterparties, while large "core" banks are more diversified and densely interconnected. A negative shock to the fundamentals of one sector reduces the value of that sector's asset and, when it is large enough, pushes exposed institutions into default and triggers portfolio liquidations that depress asset prices further through an inverse demand curve. This structure captures the interaction between interbank linkages and price-mediated externalities in a simple way and is transparent enough to deliver closed-form default thresholds and an analytical decomposition of losses.

The analysis proceeds in three steps. First, I derive explicit thresholds for the size of a sector-specific shock at which different groups of banks default. Contagion unfolds in discrete stages: (i) failure of periphery banks in the shocked sector; (ii) failure of all banks in that sector; (iii) collapse of the remaining core clique; and (iv) eventual failure of periphery banks in non-shocked sectors. At each stage, I decompose surviving banks' losses into an interbank component (arising from counterparties' defaults) and a portfolio component (arising from declines in outside-asset prices). Netting out the purely mechanical loss from the initial sectoral shock yields a natural measure of fire-sale contagion, and hence a decomposition of systemic losses into interbank versus fire-sale contributions.

Second, I calibrate the model in a simple multi-sector example and simulate the response to shocks of increasing size. Figure 6 illustrates the main finding: the model reproduces the qualitative pattern documented by Mikropoulou and Vouldis (2025). For small shocks, no bank defaults and losses are entirely mechanical. As the shock reaches the periphery default threshold, incremental contagion is transmitted primarily through interbank linkages: defaults of home-sector periphery banks impose losses on their core counterparties, while price effects from periphery liquidations remain limited. Once the shock is large enough to push the core in the shocked sector into default, the mechanism flips. Core banks liquidate diversified portfolios, inducing sizeable price declines in all sectors and generating substantial additional losses through the portfolio channel. In simulations, the interbank share of contagion is therefore highest at moderate shocks—when periphery defaults are not yet associated with large fire sales—and declines as the shock crosses successive default thresholds and core liquidations become more severe.

Finally, I run comparative statics that map network structure and balance-sheet composition into the relative weight of the two contagion channels. Holding the core–periphery architecture fixed, I vary one parameter at a time—the number of periphery banks per core (κ), the relative size of core banks (ρ), the share of core–core interbank exposures (λ), the outside-asset share (φ), market depth in the price-impact function (α), and the common loss-tolerance threshold (β). For each parameter configuration, I sweep over the full range of shock sizes, identify the regime thresholds at which new groups of banks default, and compute the interbank share of contagion at those thresholds. Figure 7 plots the resulting interbank shares by regime, and Table 1 summarises the direction of the effects. For

Table 1: Summary of comparative statics for the interbank share of contagion

Interbank share when defaults reach:	Sector-m periphery	All sector-m banks	System failure
Periphery banks per core (κ)	Decreases	Increases	Increases
Core size (ρ)	Increases	Decreases	Increases
Core–core interbank share (λ)	Decreases	Increases	Uncertain
Outside-asset share (φ)	Decreases	Decreases	Decreases
Market depth (α)	Decreases	Decreases	Decreases
Loss tolerance (β)	Increases	Increases	Increases

example, increasing κ or reducing ρ tends to raise the interbank contribution to contagion once systemic thresholds are crossed, while higher outside-asset shares or deeper markets tilt losses towards the fire-sale channel by making price impact more potent, especially in the large-shock regime.

Taken together, these results provide a simple theoretical explanation for why the dominant channel of contagion is state-dependent, and how this state dependence varies with observable system characteristics. For stress testing and macroprudential policy, this suggests that calibrations based solely on moderate shocks will understate the risks associated with common exposures, and that tools aimed at interbank linkages and those aimed at portfolio overlap should be viewed as complements rather than substitutes.

The remainder of the paper proceeds as follows. Section 2 sets up the model, and Section 3 provides an illustrative numerical example of contagion in the model with my baseline parameters. Section 4 derives the default thresholds and characterises the propagation mechanisms. Section 5 presents simulation results and comparative statics. Finally, Section 6 relates my modelling assumptions to the existing literature.

2 Model Setup

I study contagion in a stylised core-periphery banking system, combining the cascade framework of Elliott et al. (2014) with the fire-sale price impact mechanism of Gai and Kapadia (2010). The key primitives are a set of banks that hold interbank claims on one another, and risky "outside" assets backed by cash flows from different sectors of the economy.

Banks, sectors, and balance sheets. There are s sectors (e.g., business sectors or geographic regions), and n banks of two types: k large banks and $n - k$ small banks. Each small bank has a "home sector," the sector where its funding and lending relationships are concentrated. For simplicity, small banks are evenly distributed across sectors.

Banks hold two types of assets: risky "outside" assets that are claims on sectoral cash flows, and interbank claims on other banks. A common share $\varphi \in]0, 1[$ of each bank's balance

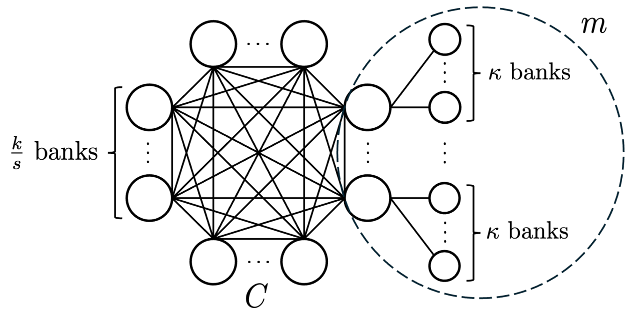


Figure 1: The interbank network structure, with periphery banks in sector m shown.

sheet is invested in outside assets, and the remaining share $1-\varphi$ in interbank claims. Small banks have balance sheet size normalised to 1, while large banks have size $\rho > 1$.

Network structure. Banks are connected through an interbank market with a core–periphery structure. The k large banks form a core clique C: each large bank has interbank links to all other large banks. The $n-k$ small banks form the periphery P: they do not lend to each other directly, but only to large banks. I therefore refer to large banks as core banks and small banks as periphery banks. The relative prominence of periphery and core institutions is summarised by the periphery-core ratio $\kappa = \frac{n-k}{k}$, where $\kappa \in \mathbb{N}$.

I assume that each periphery bank maintains a single interbank relationship with one core bank. Periphery links are sector-clustered: periphery banks in the same home sector concentrate their links on the same subset of core banks. This captures both the cost of maintaining multiple interbank relationships for small institutions and the benefits of within-sector herding for risk sharing and intermediation. This clustering allows me to assign a core bank's home sector as the sector of its periphery bank counterparties. For simplicity, I allocate core banks evenly across sectors and each sector has $n_C = \frac{k}{s}$ core banks. Periphery banks are also evenly split across their sector's core banks, so each core bank is linked to κ periphery counterparties. A graphical representation of my model is in Figure 1—for clarity, I only show the periphery banks in one sector, m.

I also allow core banks to take larger positions with other core banks than with periphery banks. Let $\lambda \in [0,1]$ denote the fraction of a core bank's interbank claims that are on other core banks. Each core bank therefore allocates $\lambda(1-\varphi)$ of its balance sheet evenly across its $n_C s - 1$ core counterparties, and allocates the remaining $(1-\lambda)(1-\varphi)$ evenly across its κ periphery counterparties. Beyond the distinction between core–core and core–periphery links, all interbank links of the same type carry the same exposure.

Correlated portfolios. In terms of outside assets, I model periphery banks as having concentrated portfolios. This captures home-sector specialisation and herding in outside assets. Let $\theta \in \left]\frac{1}{s}, 1\right]$ measure the degree of concentration, so a periphery bank holds a

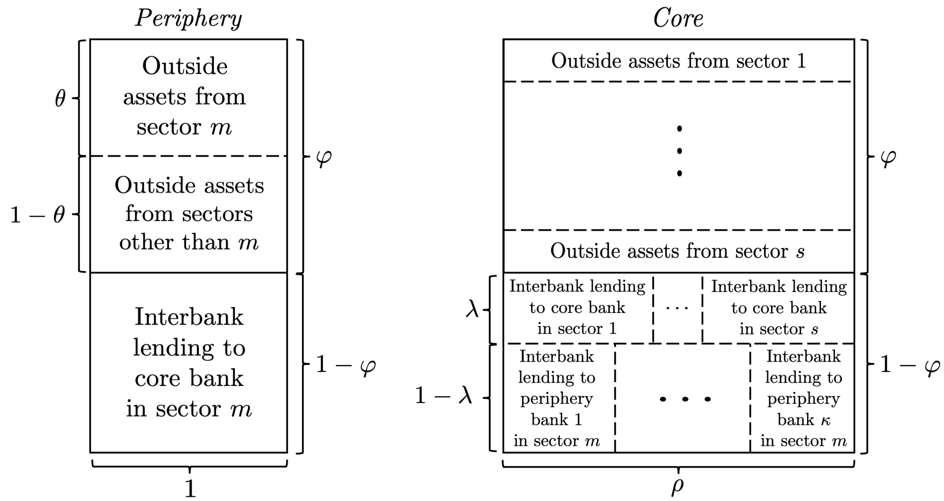


Figure 2: Asset-side balance sheets of a core and a periphery bank in sector m.

fraction θ of its outside assets in its home sector, and allocates the remaining share $1-\theta$ evenly across the other $s-1$ sectors. Higher θ captures stronger herding in the home sector; when $\theta = 1$, periphery banks in different sectors have no portfolio overlap, and periphery banks in the same sector have perfectly correlated portfolios.

By contrast, core banks are modelled as fully diversified in their outside assets. Each core bank holds the same share of its outside assets in every sector. This reflects the idea that core banks follow the same diversification rules, so their portfolios load on the same aggregate risk factor and become highly correlated. Figure 2 illustrates the asset-side composition of a core and a periphery bank.

Let $A = \varphi n_C(\rho + \kappa)$ denote the total amount of any sector's outside asset held by all banks. Let X_j be the cumulative amount of sector-j outside assets sold, and define the cumulative sales fraction $x_j = X_j/A$. Following Gai and Kapadia (2010), prices adjust according to an exponential inverse demand function

$$p_j = e^{-\alpha x_j},$$

where $\alpha > 0$ measures market depth and $x_j = 0$ corresponds to $p_j = 1$.

Shock, liquidation, and default. A shock of size δ hits some sector m, reducing the fundamental value of its outside asset by a fraction δ. This price drop

$$p_m = (1-\delta)e^{-\alpha x_m}$$

generates mark-to-market losses for all banks holding the sector-m asset, with the largest losses borne by periphery banks whose home sector is m. I summarise banks' solvency buffers

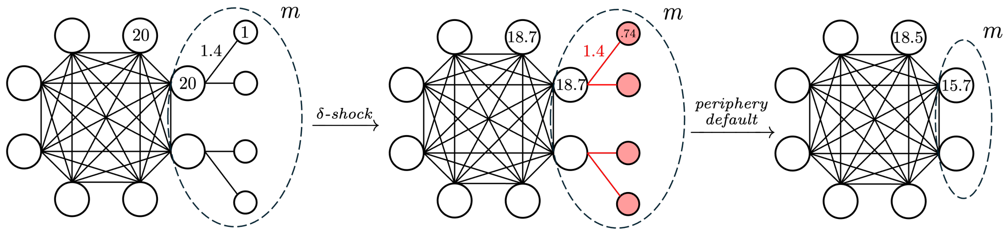


Figure 3: Small shock illustration ($\delta = 0.32$)

by a common loss-tolerance parameter $\beta \in]0, 1[$, so default occurs once the cumulative mark-to-market loss on outside assets and interbank claims is at least β of a bank's balance sheet.

Contagion channels. When a bank defaults, two channels of contagion operate. First, I assume zero recovery from defaulting banks, so it fails to repay its interbank liabilities, and its direct counterparties suffer losses on their interbank claims. Second, the defaulting bank is assumed to liquidate its entire portfolio, adding to sales pressure in the affected sectors. Through the price response function defined above, this raises the cumulative liquidation fraction x_j, depresses p_j, and generates further mark-to-market losses for all banks holding outside assets in sector j.

These losses can in turn push other banks into default, either because their outside asset values fall far enough, or because they suffer losses on interbank claims to previously defaulted counterparties. The shock therefore propagates through the system via the interaction of interbank exposures and fire-sale externalities until no further defaults occur.

3 Illustrative numerical contagion example

Before deriving the threshold conditions, I illustrate the mechanics of the model with a simple numerical example. I consider four sectors, with two core banks and four periphery banks in each sector, so the periphery–core ratio is $\kappa = 2$. I use the baseline calibration $\varphi = 0.8$, $\theta = 1$, $\rho = 20$, $\lambda = 0.3$, $\alpha = 0.8$, and $\beta = 0.25$. In this environment, each periphery bank holds 80% of its balance sheet in outside assets from its home sector, and the remaining 20% in an interbank claim on its core bank counterparty. Each core bank holds 20% of their assets in each outside sector, 6% in interbank claims on other core banks, and the remaining 14% on interbank claims on periphery banks in its home sector. I consider three shock sizes on sector m, $\delta \in \{0.32, 0.52, 0.58\}$, and describe how losses propagate in each case.

Small shock, $\delta = 0.32$ (sector-m periphery fails). Figure 3 illustrates the effect of a fundamental 32% fall in sector-m asset values. This shock mechanically generates mark-to-market losses of $32(0.2) = 6.4\%$ of total assets for each core bank and $32(0.8) = 25.6\%$ for each sector-m periphery bank. For sector-m periphery banks, this fundamental loss exceeds their loss tolerance $\beta = 0.25$, so all four of them default and liquidate their assets. Their liquidation leads to sales of $0.8(4) = 3.2$ units of the sector-m asset, about 9.1% of sector-m holdings. The price response function implies $p_m(0.32) = (1 - 0.32)e^{-0.8(0.091)} \approx 0.63$, a further 5% fall in the sector-m price.

Core banks in sector m also suffer an additional 14% loss from writing down interbank claims on their defaulted periphery counterparties. Their total losses are $6.4 + 5(0.2) + 14 = 21.4\%$, so they remain solvent, as do all banks in other sectors. Contagion is therefore confined to the periphery of the shocked sector: the initial sector-m shock wipes out the sector-m periphery but does not yet trigger a run on the core or spillovers to other sectors.

Intermediate shock, $\delta = 0.52$ (all sector-m banks fail). Figure 4 illustrates the effect of a slightly larger fundamental shock $\delta = 0.52$. The mechanical mark-to-market losses are 10.4% to core banks and 41.6% to sector-m periphery banks. As before, the sector-m periphery defaults, and imposes both a 14% interbank loss on sector-m core banks and a $(1 - 0.52)(1 - e^{-0.8(0.091)}) = 3\%$ drop in sector-m asset prices. But this time, the total loss to a core bank in sector m is $10.4 + 3 * 0.2 + 14 = 25\%$, so this additional write-down pushes them into default as well.

Their liquidation leads to sales of an additional 8 units of each sector's assets, about 22.7% of each sector's holdings. The price response function implies that $p_m(0.52) = (1 - 0.52)e^{-0.8(0.318)} \approx 0.37$, a further 8% fall in sector-m price, and $p_\ell(0.52) = e^{-0.8(0.227)} \approx 0.83$, a 17% decline in sector-ℓ prices, where $\ell \neq m$.

Remaining core banks suffer a 1.5% loss from writing down interbank claims on their defaulted core counterparties. Their total losses are $20(1 - (1 - 0.52)e^{-0.8(0.318)}) + 17(0.6) + 1.5 = 24.3\%$, so they remain solvent. The remaining periphery banks suffer a 13.6% loss in value due to fire sales, but remain solvent. Hence, contagion is confined to sector-m banks.

Large shock, $\delta = 0.58$ (system-wide failure). Figure 5 illustrates the effect of a large sector-m shock of $\delta = 0.58$. The mechanical mark-to-market losses are 11.6% to core banks and 46.4% to periphery banks in sector m. As in the previous stages, all banks in sector m

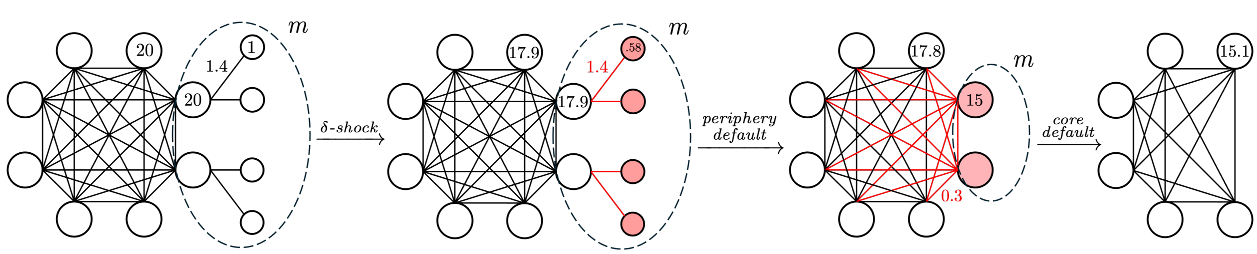


Figure 4: Intermediate shock illustration ($\delta = 0.52$)

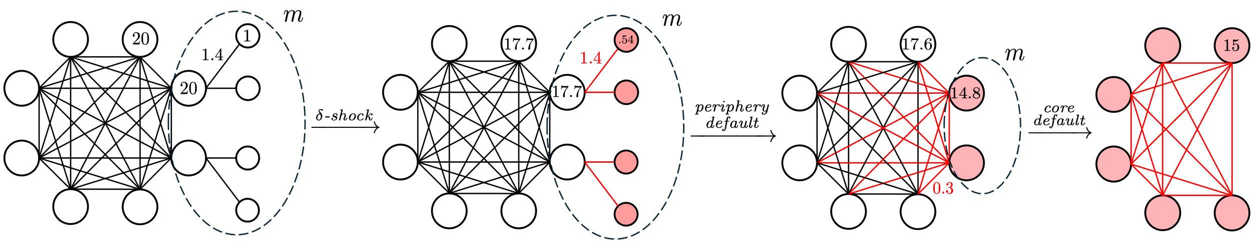


Figure 5: Large shock illustration ($\delta = 0.58$)

fail, resulting in a 1.5% interbank loss on remaining core banks, a 17% decline in sector-ℓ prices, and a further $(1 - 0.58)(1 - e^{-0.8(0.318)}) = 9\%$ fall in sector-m prices. The total loss to a remaining core bank is $11.6 + 9(0.2) + 17(0.6) + 1.5 = 25.1$, so the remaining core banks default.

The liquidation leads to sales of an additional 24 units of each sector's assets, about 68.2% of each sector's holdings. The price response function implies that $p_m(0.58) = (1 - 0.52)e^{-0.8(1)} \approx 0.22$, a further 8% fall in sector-m price, and $p_\ell(0.58) = e^{-0.8(0.845)} \approx 0.51$, a 49% decline in sector-ℓ prices, where $\ell \neq m$.

The remaining periphery banks suffer an additional 20% loss from writing down interbank claims on their defaulted core counterparties. Their total loss is $49(0.8) + 20 = 59.2\%$, so they default and the system fails.

These three examples illustrate how the same network and balance-sheet structure can generate very different patterns of contagion as the size of a sector-specific shock increases: first wiping out the periphery of the shocked sector, then all banks in that sector, and finally the full system. In the next section, I characterise the corresponding threshold shock sizes analytically.

4 Default thresholds and contagion

I proceed by characterising how a sector-m price shock of size δ propagates through interbank exposures and fire-sale externalities. Contagion unfolds in discrete stages: periphery failure in sector m, core failure in sector m, failure of the remaining core clique failure, and finally periphery bank failures in non-shocked sectors.

4.1 Initial shock

The outside asset associated with sector m suffers an exogenous proportional price drop of size δ. At this point there is no liquidation pressure, so only the sector-m asset price moves.

Consider a periphery bank with home sector m. It holds outside assets of total size φ, with share θ in sector m. After the initial shock, its mark-to-market loss as a fraction of its balance sheet is

$$L_P^{init}(\delta) = \varphi\theta\delta.$$

This implies the periphery default threshold

$$\delta_P^* = \frac{\beta}{\varphi\theta}$$

A core bank holds $\rho\varphi/s$ units of each sectoral asset, so its loss fraction from the initial shock is

$$L_C^{init}(\delta) = \frac{\varphi\delta}{s}.$$

Since $\theta > 1/s$, I have that $L_P^{init}(\delta) > L_C^{init}(\delta)$ for any $\delta > 0$, so periphery banks in sector m are the first to default. If $\delta < \delta_P^*$, the initial shock produces no failures. If instead $\delta \geq \delta_P^*$, all periphery banks in m fail.

4.2 Contagion due to periphery failure in shocked sector

Once periphery banks in m default, they sell all remaining outside assets $\varphi - \delta$. After this liquidation, the cumulative fractions sales fractions are

$$x_m^{Pliq} = \frac{\kappa\theta}{\rho+\kappa}, \qquad x_\ell^{Pliq} = \frac{\kappa(1-\theta)}{(s-1)(\rho+\kappa)}$$

so prices fall to

$$p_m^{Pliq}(\delta) = (1-\delta)e^{-\alpha x_m^{Pliq}}, \qquad p_\ell^{Pliq} = e^{-\alpha x_\ell^{Pliq}}.$$

The resulting correlated portfolio loss for a core bank, as a share of its balance sheet is

$$L_{C,corr}^{Pliq}(\delta) = \frac{\varphi}{s}(1 - p_m^{Pliq}(\delta)) + \frac{\varphi(s-1)}{s}(1 - p_\ell^{Pliq}).$$

With zero recovery, a core bank in sector m also loses its claims on its κ periphery counterparties, so its interbank loss is

$$L_{C,ib}^{Pliq} = (1-\varphi)(1-\lambda).$$

Total loss for a core bank in sector m once the periphery in m default is

$$L_C^{Pliq}(\delta) = L_{C,corr}^{Pliq}(\delta) + L_{C,ib}^{Pliq}.$$

Since p_m^{Pliq} is decreasing in δ, L_C^{Pliq} is increasing in δ on $[0,1]$. Hence, there is a unique threshold $\delta_C^* \in]0,1[$ solving

$$L_C^{Pliq}(\delta_C^*) = \beta.$$

If $\delta_P^* \leq \delta < \delta_C^*$, the periphery banks in sector m fail but the core banks in m survive and contagion stops here. For $\delta \geq \delta_C^*$, the core banks in m fail and their liquidation triggers spillovers.

4.3 Contagion due to core failure in shocked sector

When all n_C core banks in sector m default, they liquidate their diversified outside portfolio. Each defaulting core bank sells $\rho\varphi/s$ units of every sectoral asset, adding a common sales fraction

$$x^{Cliq} = \frac{n_C(\rho\varphi/s)}{A} = \frac{\rho}{s(\rho+\kappa)}.$$

Before core default, sales due to periphery liquidation in sector m are x_m^{Pliq} for the shocked sector and x_ℓ^{Pliq} for non-shocked sectors. After core default, the cumulative fraction sold is

$$x_m^{spill} = x_m^{Pliq} + x_m^{Cliq} = \frac{\kappa\theta s + \rho}{s(\rho+\kappa)}, \qquad x_\ell^{spill} = x_\ell^{Pliq} + x_\ell^{Cliq} = \frac{\kappa(1-\theta)}{(s-1)(\rho+\kappa)} + \frac{\rho}{s(\rho+\kappa)},$$

and prices fall to

$$p_m^{spill}(\delta) = (1-\delta)e^{-\alpha x_m^{spill}}, \qquad p_\ell^{spill} = e^{-\alpha x_\ell^{spill}}.$$

Core banks in sector $\ell \neq m$ have not sold assets, so their outside holdings are $\rho\varphi$, diversified across all sectors. Their correlated portfolio loss fraction after the spillover price drop is

$$L_{C,corr}^{spill}(\delta) = \frac{\rho\varphi}{s}\left(1 - p_m^{spill}(\delta)\right) + \frac{\rho\varphi(s-1)}{s}\left(1 - p_\ell^{spill}\right).$$

They also suffer interbank losses on claims to the n_C defaulting core banks in sector m, equivalent to

$$L_{C,ib}^{Cliq} = (1-\varphi)\lambda\frac{n_C}{n_C s - 1}.$$

Hence, the total loss for a core bank in $\ell \neq m$ is

$$L_C^{spill}(\delta) = L_{C,corr}^{Cliq}(\delta) + L_{C,ib}^{Cliq}.$$

Again, there is a unique threshold $\delta_{clique}^* \in]0,1[$ solving

$$L_C^{spill}(\delta_{clique}^*) = \beta.$$

If $\delta^*_C \le \delta < \delta^*_{clique}$, only the cores in m fail, so contagion ends after spillovers. Otherwise, the remaining core clique fails.

4.4 Contagion due to core clique failure

If all core banks in sectors $\ell \neq m$ are pushed into default, each of these $n_C(s-1)$ core banks liquidates its entire outside portfolio. Each core bank sells $\rho\varphi/s$ units of every sectoral asset, adding a sales fraction

$$x^{Cfail} = \frac{\rho(s-1)}{s(\rho+\kappa)}.$$

After core clique failure, cumulative sales fractions are therefore

$$x_m^{failure} = x_m^{spill} + x^{Cfail} = \frac{\kappa\theta+\rho}{\rho+\kappa}; \qquad x_\ell^{failure} = x_\ell^{spill} + x^{Cfail} = \frac{\kappa(1-\theta)}{(s-1)(\rho+\kappa)} + \frac{\rho}{\rho+\kappa},$$

so prices fall to

$$p_m^{failure}(\delta) = (1-\delta)e^{-\alpha x_m^{failure}}, \qquad p_\ell^{failure} = e^{-\alpha x_\ell^{failure}}.$$

Periphery banks in sectors $\ell \neq m$ have not sold assets yet, so their outside holdings remain φ. Their mark-to-market loss from further price drops is

$$L_{P,corr}^{failure}(\delta) = \varphi\left[\theta\left(1-p_\ell^{failure}\right) + \frac{1-\theta}{s-1}\left(\left(1-p_m^{failure}(\delta)\right) + (s-2)\left(1-p_\ell^{failure}\right)\right)\right].$$

Once their home core bank defaults, they also lose their interbank claim on the core bank, of size $L_{P,ib}^{failure} = 1-\varphi$. Hence, I have that total mark-to-market loss to a periphery bank in sector $\ell \neq m$ is

$$L_P^{failure}(\delta) = \varphi\left[\theta\left(1-p_\ell^{failure}\right) + \frac{1-\theta}{s-1}\left(\left(1-p_m^{failure}(\delta)\right) + (s-2)\left(1-p_\ell^{failure}\right)\right)\right] + (1-\varphi).$$

When $\theta = 1$, this collapses to $L_P^{failure} = \varphi\left(1-p_\ell^{failure}\right) + (1-\varphi)$, and periphery bank failure is independent of shock size. Otherwise, there is a unique threshold $\delta^*_{failure} \in]0,1[$ solving

$$L_P^{failure}(\delta^*_{failure}) = \beta.$$

For $\delta \ge \delta^*_{failure}$, all banks fail and the network collapses.

4.5 Relative size of contagion by channel

This allows me to compare the relative impact of fire-sale contagion and interbank contagion in my stylised core–periphery banking model.

In the derivations above, I decomposed the loss of a surviving bank i into a correlated portfolio component and an interbank component at each stage r. However, the correlated portfolio loss $L^r_{i,corr}(\delta)$ captures total mark-to-market losses: prices in the shocked sector take the form $p^r_m(\delta) = (1-\delta)e^{-\alpha x^r_m}$, so this loss function combines the mechanical fundamental shock $(1-\delta)$ with the additional price impact generated by liquidations.

To isolate contagion through the fire-sale channel, I net out the initial shock exposure. For any surviving bank i after stage r, define the fire-sale loss as

$$L^r_{i,fs}(\delta) \equiv L^r_{i,corr}(\delta) - L^{init}_i(\delta),$$

where $L^{init}_i(\delta)$ is the bank's loss from the exogenous sector-m price drop alone. Thus $L^r_{i,fs}(\delta)$ captures the incremental correlated portfolio losses attributed to contagion effects.

I can now aggregate $L^r_{i,fs}(\delta)$ and interbank losses across surviving banks to obtain system-wide contagion by channel. This allows me to compare the relative impact of fire-sale contagion and interbank contagion channels.

Proposition 1 (System-wide size of contagion by channel)**.** *Let $\mathcal{C}^r_{fs}$ and $\mathcal{C}^r_{ib}$ denote, respectively, system-wide correlated portfolio and interbank losses among surviving banks after stage r, computed as balance-sheet–weighted sums of individual loss fractions. Then:*

(i) After periphery liquidation in sector m only ($\delta^*_P \le \delta < \delta^*_C$):

$$\mathcal{C}^{Pliq}_{fs}(\delta) = n_C s\,\rho\, L^{Pliq}_{C,fs}(\delta) + \kappa n_C(s-1)\, L^{Pliq}_{P,fs}(\delta), \qquad \mathcal{C}^{Pliq}_{ib} = n_C\,\rho\,(1-\varphi)(1-\lambda).$$

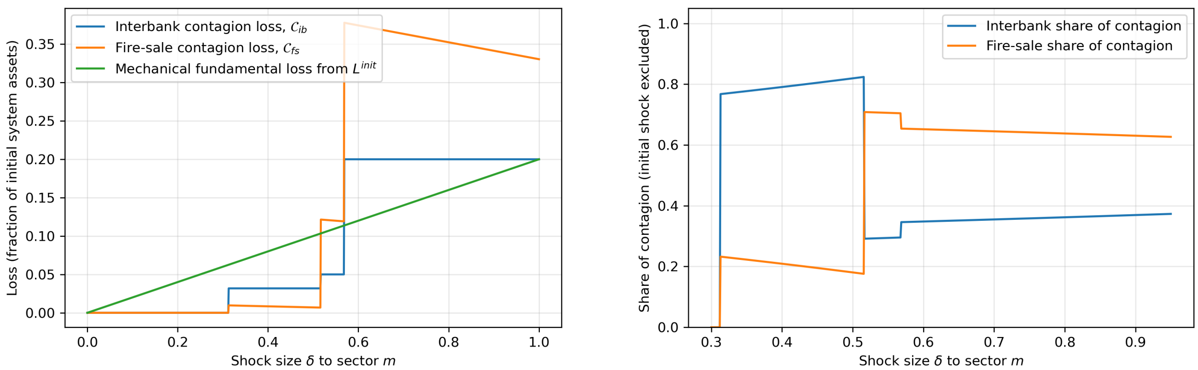
(ii) After core liquidation in sector m ($\delta^*_C \le \delta < \delta^*_{clique}$):

$$\mathcal{C}^{spill}_{fs}(\delta) = n_C(s-1)\,\rho\, L^{spill}_{C,fs}(\delta) + \kappa n_C(s-1)\, L^{spill}_{P,fs}(\delta), \quad \mathcal{C}^{spill}_{ib} = n_C(s-1)\,\rho\,(1-\varphi)\lambda\frac{n_C}{n_C s-1}.$$

(iii) After clique failure ($\delta \ge \delta^*_{clique}$):

$$\mathcal{C}^{failure}_{fs}(\delta) = \kappa n_C(s-1)\, L^{failure}_{P,fs}(\delta), \qquad \mathcal{C}^{failure}_{ib} = \kappa n_C(s-1)\,(1-\varphi).$$

Figure 6: Contagion simulation in baseline core–periphery model



(a) Absolute system loss (b) Interbank to fire-sale contagion share

Note: This figure reports the losses from a sector-specific fundamental shock in the baseline core–periphery banking system, calibrated with $s = 4$, $n_C = 2$, $\kappa = 2$, $\rho = 20$, $\varphi = 0.8$, $\theta = 1$, $\lambda = 0.3$, $\alpha = 0.8$, and $\beta = 0.25$. Panel (a) shows the absolute system loss from each channel, for each $\delta \in [0, 1]$. Panel (b) shows the share of contagion due to interbank and fire-sale channels, for each $\delta \in [0.35, 0.95]$.

5 Simulations

To quantify the relative importance of interbank versus fire-sale channels of contagion, I simulate the cascade in the baseline calibration introduced in Section 3. Throughout this section I keep the network structure and balance-sheet composition fixed, and vary either the size of the sector-m fundamental shock δ or one structural parameter at a time.

Figure 6 reports losses from a sector-specific shock when I vary only δ. Panel (a) plots the system-wide loss as a fraction of initial assets, decomposed into (i) the purely mechanical mark-to-market loss implied by the sector-m price drop, (ii) additional losses from interbank defaults, and (iii) additional losses from fire-sale price impact. For small shocks, no bank defaults and losses equal the mechanical mark-to-market loss from the initial sector shock. As derived in Section 3, at $\delta_P^* \approx 0.32$ sector-m periphery banks default, at $\delta_C^* \approx 0.52$ the home core banks fail, and at $\delta_{\text{failure}}^* \approx 0.58$ the remaining banks all fail. Each threshold adds a new set of defaults, generating discrete jumps in interbank and fire-sale losses on top of the smooth mechanical loss.

Panel (b) focuses on the composition of contagion losses. For each shock that generates any contagion ($\delta \geq 0.32$), it plots the interbank and fire-sale contagion shares

$$\omega_{ib}(\delta) = \frac{\mathcal{C}_{ib}}{\mathcal{C}_{ib} + \mathcal{C}_{fs}}, \qquad \omega_{fs}(\delta) = \frac{\mathcal{C}_{fs}}{\mathcal{C}_{ib} + \mathcal{C}_{fs}},$$

where $\mathcal{C}_{ib}$ and $\mathcal{C}_{fs}$ denote interbank and fire-sale contagion losses net of the initial mechanical shock. For shocks between the periphery and core thresholds, $\delta_P^* \leq \delta < \delta_C^*$, contagion is transmitted primarily through interbank linkages: defaults of sector-m periphery banks impose losses on their core counterparties, so $\omega_{ib}(\delta) > \omega_{fs}(\delta)$. Once the core banks in sector m fail at δ_C^* and the core clique starts liquidating diversified portfolios, fire-sale spillovers become the dominant source of contagion, and $\omega_{fs}(\delta) > \omega_{ib}(\delta)$ for all larger shocks.

Building on this baseline, I then perform comparative statics by varying one structural parameter at a time—the number of periphery banks per core κ, core size ρ, the core–core interbank share λ, the outside-asset share φ, market depth α, and loss tolerance β—while holding all others fixed. For each configuration, I sweep over shocks $\delta \in [0, 1]$ and determine which contagion regimes occur (sector-m periphery only, all sector-m banks, core clique with sector-m periphery, and full collapse). Whenever a regime r is reached, I compute the interbank contagion share $\omega_{ib}(\delta_r^*)$ evaluated at the corresponding regime-change shock δ_r^*.

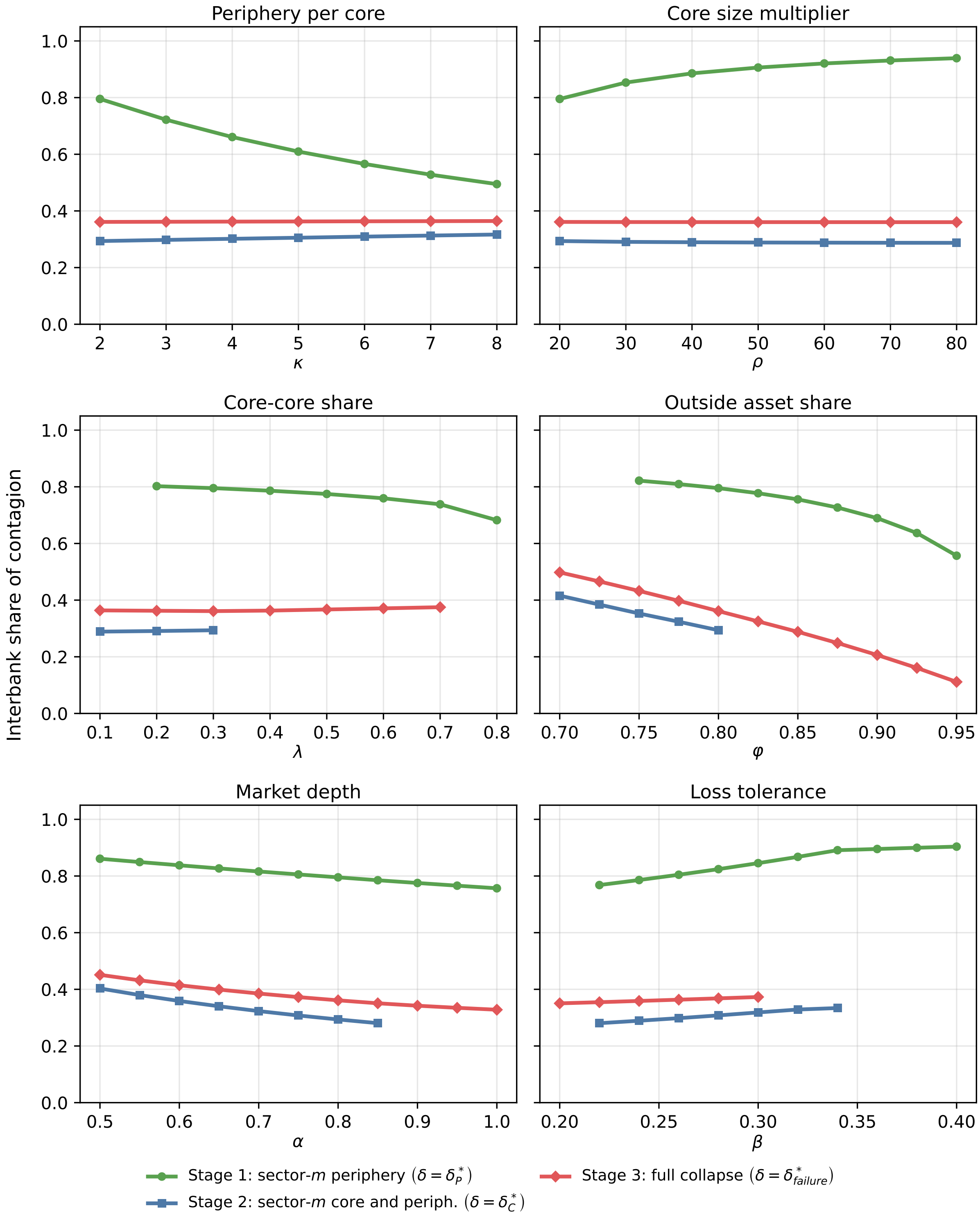
Figure 7 plots these regime-specific interbank shares for one-at-a-time parameter variation around the baseline. Each panel corresponds to a single parameter: the horizontal axis reports the parameter level, while the vertical axis reports $\omega_{ib}(\delta_r^*)$ for each regime. Within a panel, the four coloured lines trace the interbank share at the periphery-only threshold, the all-sector-m threshold, the core-clique threshold, and the full-collapse threshold, whenever that regime occurs for the given parameter level. Missing line segments indicate that the corresponding regime is skipped—for example, when the cascade jumps directly from sector-m defaults to full system collapse without a stable core-clique configuration. The systematic direction of these effects across parameters and regimes is summarised in Table 1.

6 Related Literature

This paper relates to three strands of work on financial contagion: interbank network models, fire-sale or price-mediated contagion, and the joint determination of network structure and correlated portfolios.

A large theoretical literature studies how interbank linkages transmit shocks across financial institutions. Early contributions such as Allen and Gale (2000) and Eisenberg and Noe (2001) show how bilateral exposures can generate cascades of defaults, and how clearing payments can be characterised. Subsequent work links contagion to network topology, highlighting the "robust-yet-fragile" nature of highly interconnected systems: dense networks share small shocks but can transmit large shocks widely (e.g. Acemoglu et al., 2015; Gai et al., 2011). A particular focus has been on core–periphery structures, where a densely connected core of large intermediaries is attached to a sparsely connected periphery of smaller banks. Such patterns have been documented empirically across a range of interbank markets (Boss et al., 2004; Soramäki et al., 2007; Craig and Von Peter, 2014; Fricke and Lux, 2015;

Figure 7: Interbank share of contagion at regime changes δ^*



Note: This figure reports the interbank share of contagion under one-at-a-time parameter variation in the baseline core–periphery banking system, calibrated with $s = 4$, $n_C = 2$, $\kappa = 2$, $\rho = 20$, $\varphi = 0.8$, $\theta = 1$, $\lambda = 0.3$, $\alpha = 0.8$, and $\beta = 0.25$. For each parameter level, I sweep over shocks $\delta \in [0, 1]$ and identify regime thresholds δ_r^* where a new set of banks default. At each plateau, the interbank share $\omega_{ib}(\delta_r^*)$ is computed as interbank contagion losses divided by total contagion losses.

Iori et al., 2008; Silva et al., 2016), and can be rationalised theoretically by Farboodi (2023), who shows how banks' optimal link choices to intermediate flows endogenously generate a core of highly connected intermediaries. Following Elliott et al. (2014), I represent the interbank market as a core clique attached to a periphery and use this structure to derive analytical default thresholds.

A second strand of work studies contagion through common exposures and price-mediated spillovers. Cifuentes et al. (2005) introduce a mechanism whereby banks facing capital constraints liquidate illiquid assets into a downward-sloping demand curve, generating fire sales that propagate through mark-to-market losses. Gai and Kapadia (2010) embed a similar asset-price mechanism in a network model, using an exponential inverse demand function to capture the non-linear impact of sales on prices. Greenwood et al. (2015) show how overlapping portfolios can amplify shocks through forced deleveraging, even in the absence of complex interbank linkages. I adopt a similar approach: banks hold risky claims on sectoral cash flows, and defaults force them to liquidate these assets. Prices adjust according to the inverse demand curve from Gai and Kapadia (2010), allowing me to treat interbank exposures and fire-sale externalities as two distinct channels of contagion.

A third line of research links network structure to correlated portfolios. Theoretical work shows that banks often have incentives to herd into similar assets, especially when limited liability and bailout expectations shift losses onto others. Acharya and Yorulmazer (2007) show that "too-many-to-fail" guarantees can induce banks to correlate their portfolios, while Wagner (2010) emphasises that diversification at the individual level can increase correlation at the system level. On the empirical side, Bräuning and Fillat (2019) document that large institutions subject to common diversification requirements tend to adjust towards similar portfolios, while Elliott et al. (2021) find that banks with interbank links also tend to have more correlated asset holdings. I incorporate these insights through two modelling choices. Periphery banks hold concentrated portfolios biased toward their home sectors, while core banks are fully diversified across sectors but share a common factor structure. This generates correlated portfolios between counterparties in the interbank network, consistent with the empirical pattern that bilateral exposures and portfolio overlap tend to be aligned.

Across these strands, recent work combines interbank exposures and price-mediated contagion in unified frameworks, often embedding leverage or liquidity constraints and richer behavioural responses. I contribute to this literature by analysing a stylized banking network where bilateral obligations and overlapping portfolios create distinct channels for shock propagation, providing a theoretical counterpart to the empirical pattern documented by Mikropoulou and Vouldis (2025).

7 Conclusion

I have shown, within this framework, that the main channel of financial contagion is highly state-dependent. For moderate shocks, contagion is driven largely by counterparty losses: when periphery banks default, their core creditors absorb losses, but price effects remain limited. When shocks are large enough to destabilise core institutions, the mechanism shifts. Because core banks hold diversified portfolios, their liquidations depress prices across all sectors, generating losses that extend well beyond their immediate creditors.

This state dependence arises from the interaction of network structure and portfolio composition. The comparative statics clarify which system features tilt contagion toward each channel. A larger periphery relative to the core, or greater concentration of interbank claims within the core, strengthens the role of counterparty exposures. Higher outside-asset shares, stronger price impact (thinner markets), and tighter loss tolerances increase the contribution of fire-sale spillovers, especially in large-shock regimes. Closed-form default thresholds make it possible to characterise these effects at each regime change and to decompose losses exactly into interbank and price-mediated components.

For macroprudential policy, the main implication is that tools aimed at different channels are complements rather than substitutes. Stress-testing frameworks calibrated around moderate shocks will primarily capture counterparty cascades but understate fire-sale dynamics that dominate in more extreme scenarios. Regulations targeting bilateral exposures—such as large-exposure limits or central clearing arrangements—address the interbank channel, while instruments aimed at portfolio overlap and market liquidity—such as margining rules, concentration limits, or liquidity requirements—address the fire-sale channel. Because the same network configuration can be interbank-driven under small shocks and fire-sale-driven under large shocks, focusing on one channel alone is insufficient.

Several extensions would help bring the framework closer to policy applications. Allowing for richer heterogeneity in bank size, sectoral focus, and leverage would permit institution-level measures of systemic importance. A more detailed treatment of fire sales, with multiple asset classes and endogenous liquidity provision, would better capture market dynamics during crises. Endogenising network formation and portfolio choice in response to regulation and bailout expectations would connect the static analysis here to the longer-run evolution of financial architecture under policy intervention.

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