Regulating Clearing in Networks*

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Abstract

Recent U.S. and European regulations promote centrally clearing derivatives to reduce complexity and systemic risk in the financial system. With a network model, we show that their effectiveness depends on clearing patterns. More clearing does not guarantee less systemic risk. Systemic risk can increase if multilateral netting increases at the expense of bilateral netting. We study confidential derivatives regulatory data and find evidence that contagion is less likely to start in the core but more likely to spread from the core. We introduce concepts of complexity and centrality within the financial network, exploring their implications for stability and regulatory oversight.

Keywords: Central Clearing, Systemic Risk, Interbank Networks, Central Counterparty (CCP), Over-the-Counter Trading (OTC).

JEL Classifications: G20, E50, L14

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1 Introduction

The 2008-09 financial crisis originated in malfunctioning derivatives markets, particularly credit default swaps (CDS), which were unable to absorb the wave of potential defaults propagated through a vast and complex network of derivative exposures among financial counterparties. This experience motivated the Dodd-Frank Wall Street Reform and Consumer Protection Act, aimed at curbing systemic risk. A key element of these reforms was to increase oversight of the over-the-counter (OTC) derivatives market and encourage more (central) clearing through Central Counterparties (CCPs). Ideally, all institutions would clear all exposures with a single agent (the CCP), dissolving the complex web of excess exposures and eliminating implied fragilities. However, have banks actually adopted clearing? If so, which banks and to what extent? Understanding the anatomy of clearing is crucial, as the success of reforms possibly hinges not only on the extent but also on the patterns of clearing across banks.

We construct a network model to study emerging patterns of clearing and their systemic consequences, if any. Clearing and multilateral netting have no conceptual tie to solvency in the absence of self-fulfilling events, so we focus on financial contagion that is triggered by itself (self-fulfilling contagion). Groups of banks can fail when banks rely on payments from other banks to meet their own obligations to other banks. We show that self-fulfilling failures are possible only in the presence of cycles of exposures, hence the effectiveness of regulation hinges on clearing cycles of exposures.

To illustrate how contagion gets triggered on cycles, imagine three banks, A, B, and C, interconnected through derivative exposures. A owes B, B owes C, and C owes A, say all in equal amounts. If A cannot pay B, then B cannot pay C, subsequently C cannot pay A, leading back to A's inability to pay B. This cycle creates the potential for a self-fulfilling collapse within the derivative network. However, if all three exposures in this network were cleared, *bilateral netting with the CCP* would eliminate all exposures among banks, implementing the outcome of full multilateral netting. The rationale behind the implemented regulations was eliminating unnecessary exposures, which pairs of banks may not fully internalize.

Multilateral netting through clearing is meant to address cycles that originate contagion. But contagion has two pillars: origination and cascades. Once a cyclic failure is triggered on a cycle, contagion is originated, which can now cascade outwards from the cycle across the network, via direct and indirect exposures to the cycle. The cascade features standard domino effects, possibly reaching systemic levels. Successful regulation to mitigate systemic risk must consider both pillars, origination and cascades, not only origination. First, cyclical nature of exposures must be addressed by reducing the complexity of the network of OTC exposures. This is to mitigate the origination of contagion. Second, unless all cycles can be completely eliminated, direct and indirect exposures to cycles must be moderated. This is to mitigate the cascading domino effects that spread outwards from the originating cycles. Eliminating all cycles is an impractical (and even implausible) goal without restrictive mandated clearing of all derivatives, which can also prove inefficient if reducing the flexibility of banks' insurance needs. Regulations should heighten the focus on mitigating not only origination but also cascading of contagion.

We highlight that clearing incentives may affect banks asymmetrically. This natural reaction to regulations may turn efforts irrelevant in addressing the origination pillar, but also may create *adverse consequences* in addressing the cascades pillar. When, banks' clearing rates differ exposures to cycles may decline but not disappear, while asymmetric clearing can *exacerbate* domino cascades. For example, if A owes 3 to D, and D owes 2 to A, bilateral netting would reduce the exposure to $3-2=1$. If clearing incentives are asymmetric, and say 2 is cleared but 3 is not, now D's exposure to A is 3 instead of 1, and D gets *more* exposed to the cycle between A, B, and C. Therefore contagion spreads *more*, conditional on its self-fulfilling origination. This adverse effect on the second pillar is the consequence of what we call *de-coupled clearing* between cycles and the rest. Decoupling refers to the observation that if exposures between two groups of banks are cleared at different rates, the bilaterally netted exposure of one group to the other can, in fact, increase.

Using our model as a guide, we study how the U.S. financial system has evolved in the context of derivatives exposures, and ask whether there are signs of improved stability. We use a novel and confidential dataset on derivative exposures by counterparty for the largest banks in the US which we call *core* banks.[1] This data is reported in BHCs FR-Y14Q filings, a quarterly regulatory collection which supports the Federal Reserve supervisory stress tests. We consolidate it with other publicly data available from the Bank Holding Companies (BHCs) in the U.S. (Consolidated Financial Statements for BHCs FR-Y9C).[2]

Financial networks are known to exhibit core-periphery structures. By its nature, a core-periphery network houses cycles inside the core. So we look for the anatomy of cycles inside the core to asses the regulation of the origination pillar. We look at the exposures between the core and the periphery to asses the regulation of cascades pillar.

First, to assess the effects of regulation on the cascade pillar, we evaluate how aggregate clearing patterns have evolved. We find that cleared exposures have remained stable among core banks since 2015 (the period most affected by changes in regulations) and has doubled, on average, for peripheral banks, reaching levels comparable to core banks. Our data also shows that while core banks accounted for over 95% of cleared derivatives in 2019, their share decreased to less than 80% by the end of 2022. This evidence strongly suggests an asymmetric adoption of clearing within the system, with less intensity among core banks than periphery banks. As

[1] We construct consistent time series for the largest 6 banks in the U.S. which represent almost the majority of derivative activities among U.S. banks.

[2] This data is used for example by the Office of the Comptroller of the Currency (OCC) in their Quarterly Report on Bank Derivatives Activities. See https://www.occ.treas.gov/topics/capital-markets/financial-markets/derivatives/index-derivatives.html

the periphery is known to trade sparsely with each other, the patterns strongly suggest that the regulation does indeed cause an unintended adverse consequence in the cascade pillar through de-coupling.

Second, to assess the effects of regulation on the origination pillar, we use the confidential data to show that cycles inside the core persist. Although aggregated data shows increases in clearing even by core banks, core-to-core exposures remain elevated and cyclic. This shows that the origination pillar is only partially addressed. We compute the likelihood of coordination failures originating within the core. Despite this probability has steadily declined, but not down to zero, we show it may surge dramatically and rapidly, as it did in the lead-up to the 2008 financial crisis. In other words, the risk of cyclic failure and contagion origination is not static and can escalate rapidly, hence its existence is in itself a potential concern for future stability.

Finally, we propose measures of complexity of the financial network using our confidential data. We find that the number and properties of cycles have remained relatively constant over time. This suggests a persistent vulnerability to contagion origination inside the core. Additionally, we observe significant heterogeneity across the six banks in their contribution to cycles. Some banks participate in most cycles, acting as 'failure conductors' due to their systemic relevance. Others are less involved in cycles but are net debtors to most others, making them 'failure sources.' This finding highlights the need for bank supervisors to not only monitor the number and structure of cycles but also the individual role of banks within those cycles.

In summary, the evidence we present indicates that contagion origination probability seems to be mitigated by recent pro-clearing regulations but not eliminated. The persistent cycles in the core retain the origination risk despite some mitigation, while contagion cascades has exacerbated. The periphery becomes more exposed to CCPs, CCPs become more exposed to the core, and the core retains origination risk. Even though the aggregate amount of clearing increases, systemic risk possibly increases as well, not necessarily in its origination probability but in its reach and extent. The patterns of clearing matter just as much as the amount of clearing. Our results call for renewed attention to regulation to also consider bilateral netting and the cascade potential of the network, not only multilateral netting and origination probability in the network, and to identifying the individual role of banks within the core.

Related Literature:

Recent regulatory efforts in the U.S. and Europe aimed at reducing the influence of OTC derivative markets by incentivizing the use of CCPs have sparked a renewed wave of research on the financial stability implications of this shift.[3] This research has branched into various directions. Duffie et al. (2015) examine how CCPs, given heterogeneous margin requirements, affect overall collateral demand in the system, highlighting potential distributional consequences

[3]This interest extends to legal scholarship, with recent works like McBride (2010) and Allen (2012) actively exploring the effects of CCPs and their regulation.

across intermediaries. Cont and Kokholm (2014) emphasize that while CCPs may mitigate counterparty risk, they might also reduce netting benefits across asset classes. Additionally, studies like Duffie (2015), Bignon and Vuillemey (2019), Capponi et al. (2019), Paddrik and Young (2021), Kuong and Maurin (2024) delve into CCP resolution protocols and their potential systemic consequences in times of distress.

Our approach to CCP and OTC exposures is distinct. Theoretically, we define the OTC network conditions that make contagion more probable, and based on these insights we examine the implications of incentivizing clearing and inducing potential asymmetric reactions. This asymmetry can unintentionally increase net exposures and the likelihood of self-fulfilling contagion, in spite of the overall increase in clearing. Empirically, we analyze not only the evolution of core and periphery bank exposures over the past decade but also the cyclical properties of exposure among core banks.

In the wake of the financial crisis, a wealth of literature emerged exploring the functioning and fragility of OTC markets. This research was partly spurred by a search-theoretic approach applied to asset markets, as seen in Duffie et al. (2005) and Lagos and Rocheteau (2009). Afonso and Lagos (2015), for example, studied the federal funds market using a search model to analyze how two banks engage in bilateral bargaining. Building on this tradition, Atkeson et al. (2015) introduced entry and exit into OTC derivative markets to study the resulting network characteristics. More recently, Hugonnier et al. (2019) examined the role of heterogeneity and search/bargaining frictions in OTC markets and their implications for market fragility. Our primary focus in this paper is not on the intricacies of OTC market operations, but rather on the network properties that influence the probability and extent of contagion.

More generally, our paper contributes to the growing body of literature highlighting and examining the unintended consequences of government regulations and interventions in financial networks, such as Erol and Ordonez (2017) on capital regulations and Anderson et al. (2019) on public liquidity provision.

Besides our focus on regulation and clearing, our core theory of systemic risk, while related to Caballero and Simsek (2013), presents distinct features. Notably, their model exhibits iterative *domino* contagion within a single cycle, with multiplicity arising from the feedback loop between prices and contagion. The price acts as an endogenous *popcorn* effect. See Erol and Vohra (2022) for a detailed discussion of popcorn and domino theories of contagion.[4] Our modality of contagion is a novel "dome" effect, where the dome-like architecture distributes and balances weight against minor "tremors", until a sudden and complete collapse occurs under a significant "earthquake."

Here we document the asymmetric reactions of core and periphery banks to regulations, and

[4] Additionally, complexity in Caballero and Simsek (2013) reflects price informativeness about the details of a given cycle of exposures, whereas in our work, complexity reflects intertwined cycles as multiple sources of systemic risk.

the consequences of such asymmetric reactions, not the specific reasons behind the asymmetric reactions. Spatt (2017) provides a rich discussion of a plethora of direct costs and benefits of Dodd-Frank reforms which can guide the behavior of individual banks.[5]

Section 2 details the model and conditions for contagion, illustrating cyclic behavior and asymmetric responses between core and periphery banks. Section 3 presents data on the evolution of multiplicity and exposure cycles among U.S. core banks and connects regulations promoting CCP usage to the model framework. Section 5 concludes.

2 Model

In this section we propose a variant of Eisenberg and Noe (2001) with central clearing. We first focus on highlighting the conditions for coordination failures that generate self-fulling systemic risk (origination pillar). We then discuss the conditions for clearing to reduce the likelihood of contagion, and focus on the role of asymmetric reactions between core and periphery banks (contagion pillar). We illustrate these forces with simple examples.

2.1 Setting

Environment. The financial system consists of a finite set of banks, B indexed by i and a central clearing counterparty (CCP) denoted c. We refer to any bank or the CCP as an institution and denote $I \equiv B \cup \{c\}$ the set of institutions.

Each i holds assets A_i and liabilities L_i. Asset values are subject to shocks α_i, resulting in a post-shock value of $\tilde{A}_i = \alpha_i A_i$. These shocks are jointly drawn from a distribution F with support in $\times_i[\underline{\alpha}_i, \infty)$. The CCP holds no independent assets or liabilities.

Banks are related to each other by an initial network of debt obligations. The debt of i to j is D^{**}_{ij}. The *exposure* of i to j is the asset of i that corresponds to the debt of j, $E^{**}_{ij} \equiv D^{**}_{ji}$. The CCP has no initial debt or exposure.

Clearing Exposures. Clearing an exposure of i to j by an amount e_{ij}, where $0 \leq e_{ij} \leq E^{**}_{ij}$, reduces the exposure of i to j to $E^{*}_{ij} = E^{**}_{ij} - e_{ij}$.

The cleared exposure e_{ij} is replaced by exposures to and from the CCP, increasing i's exposure to c and c's exposure to j by e_{ij}. After all clearing, the exposure of i to and from the CCP is given by $E^{*}_{ic} = \sum_j e_{ij}$ and $E^{*}_{ci} = \sum_j e_{ji}$.

The resulting exposures and corresponding debts, denoted E^{*}_{ij} and $D^{*}_{ij} = E^{*}_{ji}$ for all $i, j \in I$, are termed cleared exposures and cleared debts.

[5] In an earlier version of the paper, available upon request, we endogenize cross-bank exposures through endogenous insurance contracts, and endogenize net clearing costs by a trade-off between the liquidity risk from transparency and collateral costs from regulation.

Bilateral Netting. All cleared exposures undergo bilateral netting, resulting in the bilaterally netted exposure of $i \in I$ to $j \in I$, defined as $E_{ij} \equiv \langle E^*_{ij} - E^*_{ji} \rangle$, where $\langle \cdot \rangle = \max(0, \cdot)$. The corresponding bilaterally netted debt is given by $D_{ij} = E_{ji}$.

The bilaterally netted exposures and debts constitute the interbank assets and liabilities. The total debt of $i \in I$ is $D_i = \sum_{j \in I} D_{ij}$, and the total exposure of i is $E_i = \sum_{j \in I} E_{ij}$.

Defaults and Contagion. Shocks materialize after bilateral netting, potentially leading to a shortfall in realized interbank payments relative to obligations. Let $\tilde{E}_{ij}$ denote the interbank assets recovered by i from j, and $\tilde{E}_i = \sum_{j \in I} \tilde{E}_{ij}$ the total recovered interbank assets of i. Institution i defaults if:

$$\tilde{A}_i + \tilde{E}_i - L_i - D_i < 0 \tag{1}$$

Upon default, institution i is liquidated at a cost, reducing asset value to $\lambda \tilde{A}_i$ ($\lambda < 1$). Assuming external debt L_i is senior to interbank debt D_i, and interbank payments are pro-rata, j's recovery from i upon i's default is:

$$\tilde{E}_{ji} = \frac{D_{ij}}{D_i} \langle \lambda \tilde{A}_i + \tilde{E}_i - L_i \rangle \tag{2}$$

These rules also apply to the CCP, with the convention that $A_c = L_c = 0$.

2.2 Contagion outcomes and coordination failures

Going forward, bold symbols denote vectors or matrices of the corresponding variables. Given a system of independent and interbank assets and liabilities $(\mathbf{A}, \mathbf{L}, \mathbf{E})$, a contagion outcome under $\boldsymbol{\alpha}$ is the collection of recovered interbank assets $\tilde{\mathbf{E}}$ satisfying equations (1) and (2) for all institutions.

Multiple contagion outcomes typically exist for a given $\boldsymbol{\alpha}$, forming a lattice structure with best and worst cases. To assess self-fulfilling systemic failures, we focus on the maximum gap between these extremes. The worst outcome is termed a *coordination failure* if all banks default and settle zero payments, while no bank defaults in the best outcome.

To identify shocks $\boldsymbol{\alpha}$ enabling a coordination failure, define for each bank i:

$$\begin{aligned} \phi_i &\equiv A_i^{-1} \min \left\{ L_i + D_i \, , \, \lambda^{-1} L_i \right\} \\ \phi'_i &\equiv A_i^{-1} \left(L_i + D_i - E_i \right) \end{aligned} \tag{3}$$

Proposition 1. *A coordination failure occurs under* $\boldsymbol{\alpha}$ *if and only if* $\boldsymbol{\phi}' \leq \boldsymbol{\alpha} < \boldsymbol{\phi}$.

When $\alpha_i < \phi_i$, bank i defaults in the absence of interbank payments. This default results in no assets being distributed to other banks due to the liquidation loss. Conversely, when $\alpha_i \geq \phi'_i$, bank i remains solvent if it recovers all interbank assets. Considering these conditions for all banks, we conclude that no bank defaults in the best outcome if and only if $\boldsymbol{\alpha} \geq \boldsymbol{\phi}'$, while all banks default and make zero payments in the worst outcome if and only if $\boldsymbol{\alpha} < \boldsymbol{\phi}$. Therefore, $\boldsymbol{\alpha}$ enables a coordination failure if and only if $\boldsymbol{\phi}' \leq \boldsymbol{\alpha} < \boldsymbol{\phi}$. This region is termed the coordination failure region, and the probability of a coordination failure is defined as:

$$\Phi \equiv F(\boldsymbol{\phi}' \leq \boldsymbol{\alpha} < \boldsymbol{\phi}).$$

For example, in the case of aggregate shocks where $\alpha_i = \alpha$ for all $i \in B$, the coordination failure region simplifies to $\alpha \in [\phi', \phi)$, where $\phi' \equiv \max_i \phi_i'$ and $\phi \equiv \min_i \phi_i$, as depicted in Figure 1. The probability of coordination failure becomes $\Phi = \langle F(\phi) - F(\phi') \rangle$.

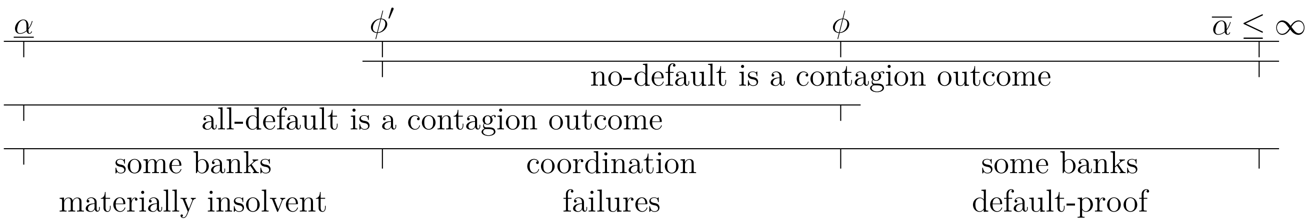


Figure 1: Coordination failure region

Proposition 2. *If $\Phi > 0$, then each bank belongs to a cycle-rooted directed tree of exposures.*

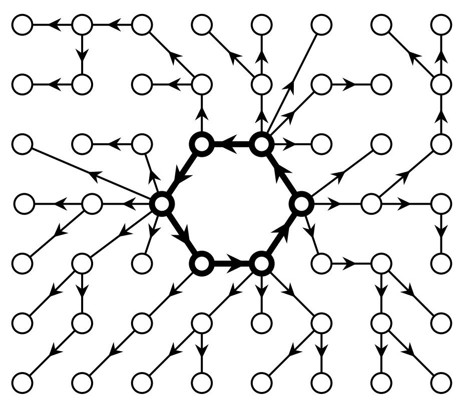


Figure 2: A cycle-rooted tree subgraph. Arrows indicate the direction of payments, which is the reverse direction of exposures.

Coordination failures arise only when the network topology allows for the transmission of distress among all banks. Figure 2 illustrates such a topology, where each bank holds exposures to other institutions. A bank without exposures is immune to interbank losses, its default becomes independent of other banks, and coordination failure is precluded.

The requirement for all banks to have exposure for a coordination failure to occur stems from our strict definition, where all banks must default. If we relax this definition to consider the default of specific banks, only those banks need exposure to the selected banks.

Applying basic graph theory, we find that the existence of coordination failures necessitates a cycle of exposures. Additionally, all banks must either participate in a cycle or be indirectly exposed to a cycle. This underscores the mechanism of coordination failures: a self-fulfilling failure of payments along a cycle that propagates through the network.

This observation is particularly pertinent to the financial system, where many networks exhibit a core-periphery structure resembling the topology conducive to coordination failures.

Systemic risk. High debt ($L_i + D_i$) and low assets (A_i) inherently increase a bank's fragility, making both ϕ_i' and ϕ_i measures of fragility.

Clearing, while affecting individual debt and exposure levels, leaves the net interbank position ($D_i - E_i$) unchanged. This is due to clearing merely shifting counterparties from banks to the CCP without altering the overall financial position. Consequently, the lower bound ϕ_i', determined by external assets and equity, remains unaffected by clearing. We term ϕ_i' the independent fragility of bank i, as when $\alpha_i < \phi_i'$, i defaults even with full interbank asset recovery. Conversely, ϕ_i is termed interdependent fragility, as when $\phi_i' < \alpha_i < \phi_i$, i's default depends on its interbank asset recovery.

In our empirical analysis, we report both $\boldsymbol{\phi}'$ and $\boldsymbol{\phi}$. Focusing on interdependent and self-fulfilling failures, we simplify the theoretical analysis by assuming $\boldsymbol{\phi}' < \underline{\boldsymbol{\alpha}}$ for the initial debt obligations and the shock distribution. This means that no bank defaults if other banks do not. Hence all systemic failures coordination failures. To further emphasize coordination failures, we assume that on the path of play, the coordination failure materializes whenever $\boldsymbol{\alpha} < \boldsymbol{\phi}$, and no bank defaults otherwise.

2.2.1 Example

Consider three banks $B = \{1, 2, 3\}$. Each bank has assets $A_i = 4$ and liabilities $L_i = 3$. The exposures are by $D_{12}^{**} = D_{23}^{**} = D_{31}^{**} = 3$ and $D_{21}^{**} = D_{32}^{**} = D_{13}^{**} = 1$. Assume that the shock is aggregate $\alpha_i = \alpha$ for all i. All banks are symmetric so we can drop the indices.

Figure 3 displays the network of exposures (left panel) and the bilaterally netted exposures (right panel) exposures, with arrows indicating debt direction.

The liability of each bank is 3. The total exposure of each bank is $3+1 = 4$ and the total debt of each bank is $3 + 1 = 4$. So regardless of clearing, $\phi' = \frac{3+4-4}{4}$. Assuming $\underline{\alpha} = \frac{3}{4}$, no-default is always an outcome, as $4\alpha > 3$ ensures sufficient funds to cover both interbank and senior debt if a bank receives all its interbank exposures. We now analyze how ϕ responds to clearing.

Absent clearing, each bank's bilaterally netted exposure is 2. In the no-default outcome, each bank receives $\alpha A + E = 4\alpha + 2 > D + L = 5$, as shown in Figure 4 (left panel).

Conversely, without receiving $E = 2$, a bank cannot fulfill its debt if $4\alpha < 5$, leading to liquidation when others default and $\alpha < \frac{5}{4}$. With low liquidation values ($\lambda < \frac{3}{5}$), liquidated assets only cover senior debt ($L = 3$), leaving nothing for interbank debt (D), resulting in full

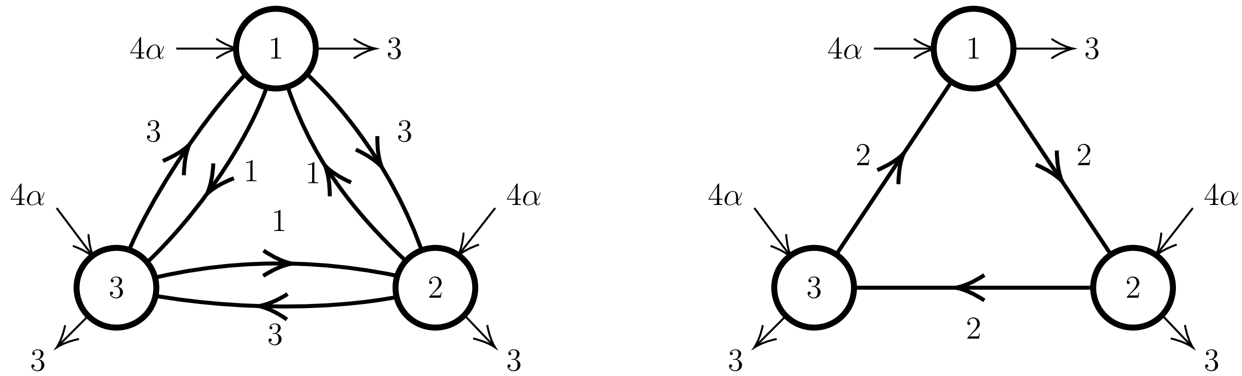


Figure 3: The system before and after bilateral netting

default as shown in Figure 4 (right panel).

In this example, $\phi = \frac{L+D}{A} = \frac{5}{4}$, and the probability of coordination failure is $\Phi = F(\frac{5}{4})$. The condition $\lambda < \frac{3}{5}$ ensures that interbank default leads to systemic failure.

In summary, full default occurs when (i) Aggregate shocks are sufficiently adverse compared to total liabilities ($\alpha < \frac{5}{4}$), (ii) default triggers costly liquidation ($\lambda < \frac{3}{5}$), (iii) there exists a cycle of exposures (as seen in Figure 3).

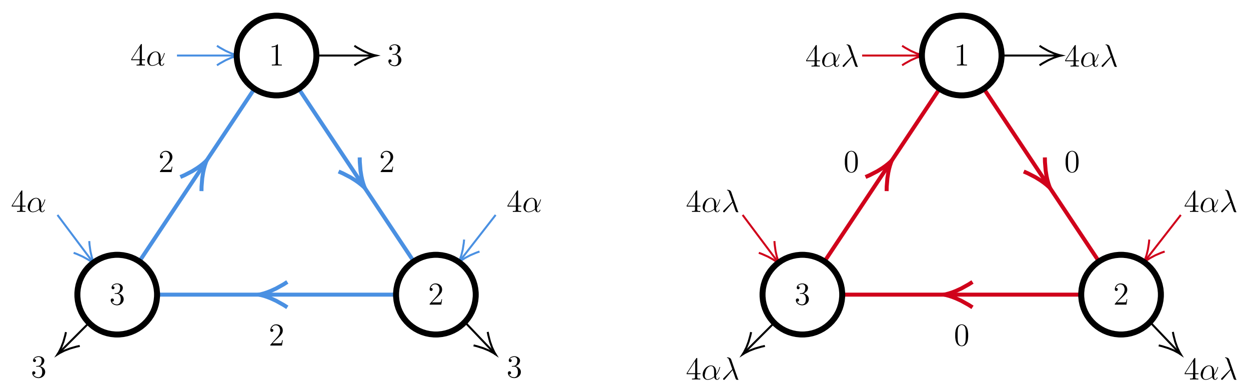


Figure 4: Example of a coordination failure under conditions $3 < 4\alpha < 3 + 2$ and $4\alpha\lambda < 3$. Left panel: all pays given $3 < 4\alpha$. Right panel: no one pays given $4\alpha < 5$ and $4\alpha\lambda < 3$.

Role of Clearing in Coordination Failures. Complete clearing of all exposures prevents coordination failures. However, complete clearing is often impractical. We illustrate the effects of partial clearing using our example.

Suppose banks clear their large exposures (3) but not their small ones (1). This results in *pro-cyclic clearing*, where the subsequent bilaterally netted exposures decrease in volume in the original (i.e. absent clearing) direction of bilaterally netted exposures, as shown in Figure 5 (left panel). In this scenario, a bank cannot pay its interbank debt if $4\alpha < 4$, leading to coordination failure when $\alpha < 1$. Formally, $\phi = 1$, and the probability of coordination failure decreases from $F(\frac{5}{4})$ to $F(1)$.

Alternatively, if banks clear their small exposures (1) but not their large ones (3), we have *counter-cyclic clearing*, where subsequent bilaterally netted exposures increase in volume in the the original direction, as shown in Figure 5 (right panel). Here, a bank cannot pay its interbank debt if $4\alpha < 6$, leading to a coordination failure when $\alpha < \frac{6}{4}$. Formally, $\phi = \frac{6}{4}$, and the probability of coordination failure increases from $F(\frac{5}{4})$ to $F(\frac{6}{4})$.

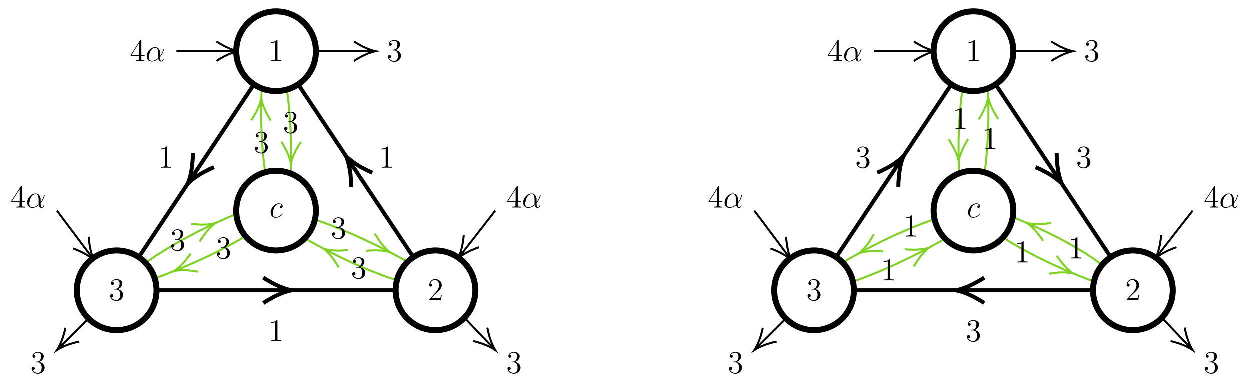


Figure 5: Partial clearing. Left panel: system after pro-cyclic clearing. Exposure 3s are cleared and netted out through bilateral netting with the CCP. The coordination failure conditions become $3 < 4\alpha < 3 + 1$ and $4\alpha\lambda < 3$, reducing Φ. Right panel: system after counter-cyclic clearing. The exposure 1s are cleared and netted out through bilateral netting with the CCP. The coordination failure conditions become $3 < 4\alpha < 3 + 3$ and $4\alpha\lambda < 3$, increasing Φ.

Remark: The impact of clearing on coordination failures and contagion depends on details beyond the amount of clearing. As we have illustrated, clearing that increases bilaterally netted exposures along the direction of the cycle exacerbates coordination failures.

To generalize the insight, consider a cycle with clockwise debt D and counter-clockwise debt $D' < D$. The original bilaterally netted exposures absent clearing are $D - D'$ clockwise.

Counter-cyclic clearing is clearing an exposure $d' \leq D'$ against the original bilaterally netted exposure increases exposures along the cycle, changing $D - D' > 0$ to $D - (D' - d') > D - D'$. Counter-cyclic clearing exacerbates coordination failures.

Pro-cyclic clearing is clearing an exposure $d \leq D$ in the direction of the original bilaterally netted exposure can either decrease the bilaterally netted exposure to $(D-d)-D' > 0$ or reverse the cycle's direction with bilaterally netted debt $D' - (D - d)$ counter-clockwise. However, if $D \geq d > 2(D - D')$, the resulting bilaterally netted exposure $D' - (D - d)$ exceeds the original $D - D'$, increasing exposures along the cycle.

Thus, for pro-cyclic clearing to be beneficial, the cleared amount must not be too large. This poses a risk when exposures are close to each other and bilaterally netted amounts are small relative to original un-netted amounts: $D \geq 2(D - D')$.

2.2.2 Endogenous clearing and equilibrium

Each bank i consist of a unit measure of bankers indexed $u \in i$. We also denote $b(u) = i$. Each banker u makes and manages contracts with a mass of bankers m_u from other banks. The contracts are undertaken on behalf of banks. For $v \in m_u$, the contract is an independent random variable $(\kappa_{uv}, \kappa_{vu})$ describing the payment κ_{uv} that b_u is promised and the payment κ_{vu} that b_v is promised. These contracts underlie the exposures of banks:

$$E_{ij}^{**} = \int_{u \in i} \int_{v \in m_u \cap j} \kappa_{uv} \mathtt{d}v \mathtt{d}u$$

Each banker is promised compensation as a function of the net gains from the contracts that u manages. This is,

$$\pi_u = \pi \left(\int_{v \in m_u} (\Gamma_{b(v)} \kappa_{uv} - \kappa_{vu}) \mathtt{d}v \right)$$

where $\Gamma_j = \frac{\tilde{D}_j}{D_j}$ is the recovery rate of exposed banks from bank j.[6]

If i defaults, there is nothing left to pay bankers. So u's settled compensation is $\tilde{\pi}_u = \mathbb{1}[\Gamma_i > 0] \times \pi_u(\Gamma_{-i})$.[7] The vector of recovery rates $\mathbf{\Gamma} = ((\Gamma_j)_{j \in B}, \Gamma_c)$ is an aggregate variable.

Contracting and clearing are done at the banker level. Infinitesimal bankers have no effect on $\mathbf{\Gamma}$. In making contracting and clearing decisions, u maximizes its utility from $\tilde{\pi}_u$ given the equilibrium $\mathbf{\Gamma}$. Γ_j can be seen as the stochastic price of stability of j akin to Walrasian prices.[8]

Our focus is clearing and we fix the contracts. Clearing is endogenous. Net exposed banker in a pair decides. This is, if $\mathbb{E}[\kappa_{uv} - \kappa_{vu}] > 0$, u is said to be exposed to v. In this case, u decides whether to clear the contract or not and bears the net cost of clearing κ_{uv}. This cost can be positive or negative and it is defined in utils for simplicity.

The net cost κ_{uv} can have several components. For example if the CCP entails lower counterparty risk than v's bank, u is incentivized to clear the contract. This cost or benefit is reflected in changing $\Gamma_{b(v)}\kappa_{uv}$ into $\Gamma_c \kappa_{uv}$ in π_u. Other costs are regulatory costs, collateral costs, transparency, funding costs, CCP membership, margin calls, contract standardization costs, and benefits like reduced risk weights in capital requirements.[9] We are agnostic on the precise de-

[6] The compensation can be defined more generally. It can include a wage. It can depend or not depend on recovery rates.

[7] There is pro-rata distribution within the bank when total compensation can not be provided. This is, each $u \in i$ gets $\tilde{\pi}_u = \pi_u \min \left\{ 1, \frac{\max\{0, \tilde{A}_i - L_i + \tilde{E}_i - D_i\}}{\int_i \pi_{u'} \mathtt{d}u'} \right\}$.

[8] For example, if all bankers in a bank were completely identical, then it would be as if there is a representative banker and the bank takes Γ_{-i} as given. In this sense, banks are "stability-takers" in the model.

[9] There are opportunity costs of collateral due to margin requirements. The CCP and the OTC counterparties have different requirements regarding collateral. This would be proxied by $\mathbb{E}[\Gamma_{i/c}\kappa_{vu}]$ and $\mathbb{E}[\Gamma_{b(v)/c}\kappa_{vu}]$.

There are regulatory costs. Cleared derivatives are subject to lower risk weights in capital requirements. Then keeping a contract OTC can create shadow costs on the banker through restrictions placed on trades by the bank's risk division whose objective is to ensure regulatory compliance at the bank level. This cost could be proportional to $\mathbb{E}[\kappa_{uv} - \kappa_{vu}]$ as the reduction in exposures via clearing. This cost also depends on the size of terminants of costs. In general, costs take the form $c_{uv}(\mathbf{\Gamma})$ given that the contracts are fixed. The cost is the sole determinant of clearing since $\tilde{\pi}_u$ does not depend on u's decision on clearing. Then the cleared amount out of the exposure of i to j, E_{ij}^{**} is

$$e_{ij}(\mathbf{\Gamma}) = \int_{u\in i}\int_{v\in m_u\cap j} \kappa_{uv}\mathbb{1}\left[\mathbb{E}[\kappa_{uv}-\kappa_{vu}]>0 \wedge \mathbb{E}\left[c_{uv}(\mathbf{\Gamma})\right]<0\right]\mathtt{d}v\mathtt{d}u$$

Then the resulting exposure network after bilateral netting, $\mathbf{E}(\mathbf{\Gamma})$, and the distribution of the shock $\boldsymbol{\alpha}$ determine $\mathbf{\Gamma}$ via the contagion dynamics described before, $\mathbf{\Gamma} = \Psi\left(\mathbf{E}(\mathbf{\Gamma}), \boldsymbol{\alpha}\right)$. This is the "market-clearing" condition. A similar condition arises also when contracts are endogenous.

As we have shown in the previous section, more clearing does not necessarily reduce the probability of coordination failures. Moreover $\mathbf{E}(\mathbf{\Gamma})$ is not even necessarily continuous in $\mathbf{\Gamma}$, for example when c_{uv} is homogenous across pairs. Existence of equilibrium is not guaranteed. We leave identifying general conditions that yield existence to future work.

We consider constant costs $c_{uv}(\mathbf{\Gamma}) \equiv \delta_{uv}$. This is natural in the context of coordination failures. All defaults are perfectly correlated and so the relative stability gain of clearing is $\Gamma_c - \Gamma_{b(v)} = 0$.

Theorem 3. *A (general) equilibrium exists. In it, for any u and $v \in m_u$, the contract $(\kappa_{uv}, \kappa_{vu})$ is cleared if and only if $\mathbb{E}[\kappa_{uv} - \kappa_{vu}] > 0$ and $\delta_{uv} < 0$.*

Our empirical analysis shows that large banks' clearing is less elastic to regulatory changes that influence costs. This is possibly because reduced risk-weights do not incentivize banks with high equity which are not bind by capital requirements. These banks may have larger need for flexibility as they trade in many different asset classes and have exotic derivative contracts that CCPs may refuse to clear. They may also be more subject to more scrutiny by the market and prefer to protect privacy. These indicate positive δ for large banks.

2.3 Core-periphery

Financial networks often exhibit a core-periphery structure, characterized by a small group of densely connected core banks linked to sparsely connected periphery banks with minimal or no connections among the periphery banks themselves. We assume that the initial system of debt obligations has a core-periphery structure, denoting K the core and P the periphery. Notably, most cycles in core-periphery structures involve the core due to sparse connections within the periphery. We make this point more stark for clarity and assume that there are no exposures

the bank as systemically important banks have higher capital adequacy ratio.

There are transparency costs depending on the type and size of the contract. Clearing generally improves transparency. But banks prefer to protect the privacy of their positions for several reasons. The large trades of large banks can suffer from more inference by the market. This cost would depend on the size of the contract $\mathbb{E}[\kappa_{uv} + \kappa_{vu}]$ as well as the size of the bank.

between periphery banks and there are no cycles involving the periphery banks. Also note that the core-periphery structure surprisingly aligns with the topological conditions for coordination failures outlined in Proposition 1 and illustrated in Figure 2.

The benchmark case is the absence of clearing, with coordination probability denoted Φ^*. This corresponds to a regulatory environment where all clearing costs are positive. We now analyze changes in systemic risk under different cost scenarios, reflecting the impact of regulations on clearing incentives and, consequently, systemic risk.

Theorem 4. *(Asymmetric clearing) If the core does not clear, coordination failure probability increases. This is,* $\Phi \geq \Phi^*$ *if* $\delta_{uv} > 0$ *for all* $u \in i \in K$.

We illustrate implications of this result by simplifying costs further. We assume that relative clearing costs depend on the types of banks only instead of the bankers: δ_{KK} (core-core), δ_{KP} (core-periphery), and δ_{PK} (periphery-core). Note that δ_{PP} is irrelevant due to the absence of periphery-periphery exposures. We also disregard asymmetric clearing costs within the core for clarity. Asymmetry within the core would introduce pro-cyclic or counter-cyclic clearing which we discussed earlier.

Proposition 5. *Relative to no-clearing benchmark* Φ^*, *the endogenous coordination failure probability* Φ *satisfies the following:*

- *Core clearing: If* $\delta_{KK} < 0$, *then* $\Phi = 0 \leq \Phi^*$.
- *Coupled clearing: If* $\delta_{KK} > 0$, *and* $\delta_{PK}\delta_{KP} > 0$, *then* $\Phi \leq \Phi^*$.
- *Decoupled clearing: If* $\delta_{KK} > 0$, *and* $\delta_{PK}\delta_{KP} < 0$, *then* $\Phi \geq \Phi^*$.

Under core clearing, all exposures within the core are cleared, eliminating cycles within the core. Since cycles are in the core and coordination failures can be triggered only with cycles, systemic risk is eliminated at its source.

Under coupled clearing, exposure between the core and the periphery are either both cleared or both not cleared. The latter is the benchmark case. The former is the clearing of exposures between the core and the periphery. This facilitates multilateral netting, reducing core-periphery exposures and mitigating the propagation of cyclic failures originating in the core.

Under decoupled clearing, one-directional clearing decreases bilateral netting between the core and the periphery and increases exposures while leaving core cycles intact. Consequently, cyclic failures that start at the core propagate more either through the CCP or directly to the periphery.

This analysis highlights the crucial role of multilateral netting in mitigating systemic risk. When clearing is limited to only one direction between the core and periphery, the system fails to achieve multilateral netting but reduces bilateral netting, leading to an increased susceptibility to coordination failures.

When clearing costs inside the core are heterogeneous, the details of the cycles inside the core determine whether clearing is pro-cyclical or counter-cyclical. This can amplify or attenuate the effects in Proposition 5.

2.3.1 Example

The example in Section 2.2.1 highlighted the importance of clearing direction within core banks for the likelihood of coordination failures. While we imposed specific clearing patterns in that example, patterns could be rationalized by specific heterogeneously structured costs along the cycle.

Now, we illustrate coupled and decoupled clearing. Consider a financial system with three core banks $K = \{1, 2, 3\}$ and three periphery banks $P = \{4, 5, 6\}$. Shocks are aggregate, $\alpha_i = \alpha$ for all i. Core banks have assets $A_i = 4$, liabilities $L_i = 3$, and cyclic exposures within the core: $D^{**}_{12} = D^{**}_{23} = D^{**}_{31} = 2$, with $D^{**}_{ij} = 0$ otherwise. This core cycle can trigger a coordination failure if the shock α is sufficiently low. We assume large liquidation costs, $\lambda < \frac{3}{7}$.

Periphery banks have assets $A_i = 2$, senior liabilities $L_i = 3$, and no exposures among themselves. Exposures between the core and periphery are bidirectional, as illustrated in Figure 6 (left panel).

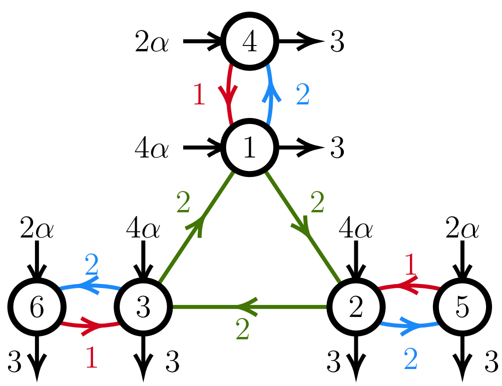


Figure 6: No clearing and bilateral netting. Arrows indicate the direction of payment flows.

Without clearing, after bilateral netting, each core bank owes 2 to its core creditor along the cycle and 1 to its periphery counterparty, resulting in total interbank debt $D_K = 3$. Periphery banks, due to netting, owe nothing ($D_P = 0$). This post-netting system is shown in Figure 6 (right panel). Without clearing, we compute $\phi_K = \frac{3+3}{4} = \frac{3}{2}$ and $\phi_P = \frac{3+0}{2} = \frac{3}{2}$, leading to a coordination failure probability of $F(\frac{3}{2})$.

We now consider endogenous clearing scenarios based on Proposition 5. Assuming $\delta_{KK} > 0$, we study the divergence in the incentives of the core and the periphery to clear.

If $\delta_{PK} < 0$ and $\delta_{KP} < 0$, core-periphery exposures are cleared and clearing is coupled. The resulting system is shown in Figure 7. In this example, ϕ_K and ϕ_P remain unchanged after clearing, and thus $\Phi = F(\frac{3}{2})$.

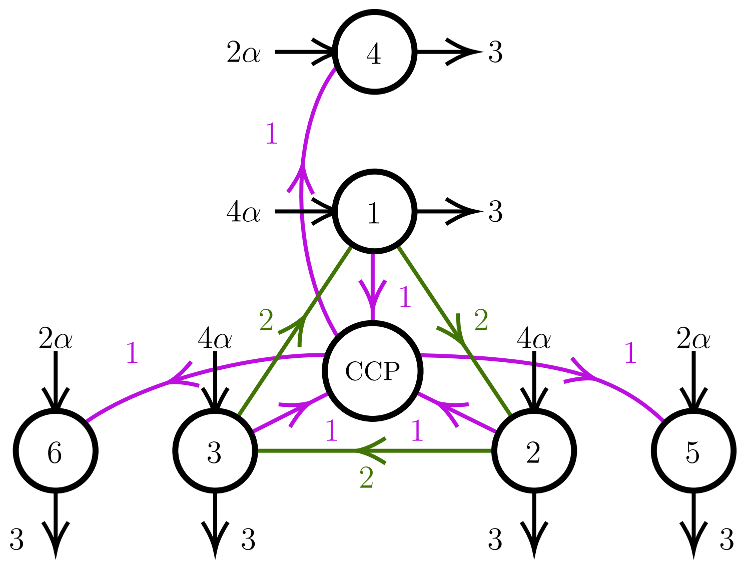


Figure 7: $\delta_{KK} > 0$ and $\delta_{PK}, \delta_{KP} < 0$

Consider the case of decoupled clearing where $\delta_{PK} < 0 < \delta_{KP}$. Here, periphery banks clear their exposures to the core, while core banks do not clear their exposures to the periphery. This implies that periphery banks prefer to be paid by the CCP instead of the core, while core banks prefer to be paid by the periphery rather than the CCP.

The resulting system is shown in Figure 8. After clearing, a core bank's exposure to its periphery counterparty is 1, but it now owes 2 to the CCP instead of the periphery bank. The periphery, in turn, is exposed to the CCP by 2.

Decoupling eliminates bilateral netting between the core and periphery, increasing the total debt of both core banks (from $D_K = 3$ to $D_K = 4$) and periphery banks (from $D_P = 0$ to $D_P = 1$). This impacts the likelihood of coordination failure, with the new interdependent fragility levels being $\phi_K = \frac{3+4}{4} = \frac{7}{4}$ and $\phi_P = \frac{3+1}{2} = 2$. The probability of coordination failure increases from $F(\frac{3}{2})$ without clearing to $F(\frac{7}{4})$ with decoupled clearing.

Finally, consider the reverse decoupled clearing scenario where $\delta_{PK} > 0 > \delta_{KP}$. Here, core banks clear their exposures to the periphery, while periphery banks do not clear their exposures to the core.

This scenario is depicted in Figure 9. After clearing, a periphery bank's exposure to its core counterparty increases to 2, and it now owes 1 to the CCP instead of the core bank. The core, in turn, is exposed to the CCP by 1.

As in the previous decoupling case, bilateral netting between the core and periphery is eliminated, and the total debt of both core and periphery banks increases. This leads to the same

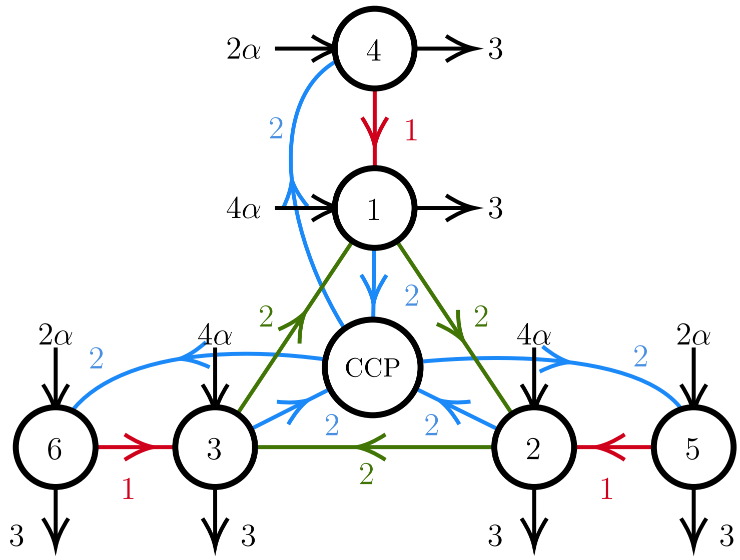


Figure 8: Decoupling under $\delta_{KK} > 0$ and $\delta_{PK} < 0 < \delta_{KP}$

increase in the likelihood of coordination failure, from $F(\frac{3}{2})$ without clearing to $F(\frac{7}{4})$ with decoupled clearing.

The similarity in outcomes between the two decoupling scenarios emphasizes that the direction of clearing in a decoupled system does not fundamentally alter the increase in systemic risk caused by the loss of bilateral netting benefits. Both scenarios highlight the importance of aligned and balanced clearing to achieve multilateral netting and effectively mitigate coordination failures.

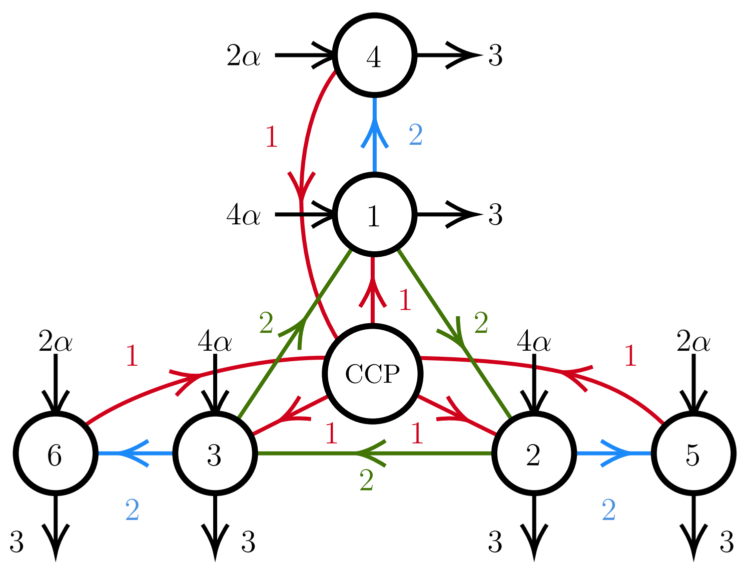


Figure 9: Decoupling under $\delta_{KK} > 0$ and $\delta_{PK} > 0 > \delta_{KP}$

Decoupled clearing, while aiming to achieve multilateral netting through CCPs, can be detrimental to bilateral netting. When applied between the core and periphery asymmetrically, it fails to provide any benefits in terms of multilateral netting. Conversely, clearing within the core has the potential to eliminate coordination failures altogether.

Therefore, understanding who clears what and in which direction is crucial for assessing the impact of clearing on coordination failures. The choice of clearing strategy should be carefully considered, as it can either mitigate or exacerbate systemic risk.

It is important to note that eliminating coordination failures does not guarantee the elimination of system-wide failures. Systemic failures can still occur due to solvency issues, even in the absence of cycles. However, the presence of cycles introduces an additional layer of vulnerability through contagion, making the system more susceptible to cascading defaults.

3 Empirical Evidence

In this section, we outline the regulatory reforms, present the relevant data, and discuss the key empirical findings, connecting them to the predictions of our model.

3.1 Clearing, Reforms, and Incentives

The 2008 financial crisis led to a series of regulatory reforms aimed at enhancing the resilience of the financial sector. These reforms encompassed changes in capital and liquidity requirements, with a particular focus on reducing counterparty credit risk through increased central clearing. This emphasis on central clearing was implemented through two key regulatory mechanisms:

1. **Restrictions:** Standardized over-the-counter (OTC) derivatives are mandated to be cleared through central counterparties (CCPs).[10]

2. **Incentives:** Non-cleared derivatives are subject to higher capital (higher risk-weights) and collateral requirements.[11]

The initial proposal for reform was made in 2009, when G-20 Leaders agreed that all standardised OTC derivative contracts should be traded on exchanges or electronic trading platforms, where appropriate, and cleared through central counterparties (see FSB (2010)). Most of the final rules

[10] A centrally cleared derivative contract is defined as "... a derivative contract is an exposure associated with an outstanding derivative contract that an institution, or an institution that is a clearing member has entered into with a central counterparty (CCP), that is, a transaction that a CCP has accepted." (see www.federalreserve.gov/reportforms/forms/FR_Y-9C20191231_i.pdf, link last accessed 05/24/2024). In our framework, these are the cleared exposures. Any other derivative contract is called OTC.

[11] Derivatives cleared through a CCP incur not only the capital charge due to the trade exposure but also a default fund capital charge (on average small).

were implemented between 2012 and 2015.[12,13] For most of the analysis, and consistent with our reading of the changes in the financial system, we focus on the period that starts in 2015.Q1 as the post-reform period.

Our model is sufficiently versatile to reflect changes in the regulatory environment through adjustments in the relative clearing costs $\{\delta_{KK}, \delta_{KP}, \delta_{PK}\}$. These costs encapsulate the full range of regulatory changes, so we do not attempt to measure them directly. Instead, we assume values for these costs that are consistent with the observed reactions of the network and then use these inferred costs, along with the observed network behavior, to make predictions about systemic risk. In the following sections, we present the data we utilize and the predictions derived from our analysis.

3.2 Data Sources

In order to analyze systemic risk in the financial network, the connection across the most important players, and the role of central counterparties, we work primarily with two data sources: (1) the Consolidated Financial Statements for Holding Companies (FR-Y9C) and (2) the Capital Assessments and Stress Testing Data (FR-Y14Q - Schedule L "Trading and Counterparty").[14] Both data sets have a quarterly frequency.[15] The FR-Y9C is (for most part) public and collects financial data (balance sheet, income statement, and several other schedules including institution level values of off-balance sheet items) at the bank holding company (BHC) level on a consolidated basis. We use non-confidential schedules for our analysis. Only bank holding companies ("banks") with more than $3 billion in assets are required to report. Our second data source, the FR-Y14Q (schedule L), is confidential and used to support supervisory stress testing models and for continuous monitoring by the Federal Reserve. We gained access to the "Trading and Counterparty" schedule (schedule L).[16] Schedule L includes key information on counterparty risk and it is submitted by banks with significant derivative activity and allows us to construct a consistent time series for 6 reporting banks (some other banks start reporting after 2019 and not

[12] We provide an extended account of the changes in regulation that affected OTC derivatives in the Appendix. See also the Financial Stability Board (FSB) progress reports published since 2010 and Ghamami and Glasserman (2017).

[13] The original proposal also included collateral costs for OTC derivatives via margin requirements but those reforms were postponed several times and implemented only recently.

[14] We describe these two sources and the variables we use in more detail in the Appendix.

[15] The FR-Y14Q Schedule L started to be reported at the quarterly frequency after 2014.Q2.

[16] Banks that comply with the following requirements submit these regulatory forms: (1) have aggregate trading assets and liabilities of $50 billion or more, or aggregate trading assets and liabilities equal to 10 percent or more of total consolidated assets, and (2) are not "large and noncomplex firms" under the Board's capital plan rule. A large and noncomplex firm is a BHC with total consolidated assets of at least $50 billion but less than $250 billion, total consolidated nonbank assets of less than $75 billion, and is not a U.S. Globally systemically important bank (GSIB).

in a consistent frequency).[17] These are the largest banks in the U.S. when sorted by assets: J.P. Morgan Chase, Bank of America, Wells Fargo, Citibank, Morgan Stanley, and Goldman Sachs. We call the group of six banks for which we construct the full picture of counterparty exposure in our sample as "core" banks. We think of core banks as large and interconnected banks that pose systemic risks. Of particular importance, this schedule provides detailed information at the counterparty level.

We make use of primarily two non-confidential schedules from the FR-Y9C report: schedule HC-R ("Regulatory Capital") and schedule HC-L ("Derivatives and Off-Balance Items"). Using the schedule HC-R we can obtain estimates of derivative activity by risk-weights. Starting in 2015, the report makes a distinction between over-the-counter derivatives and centrally cleared derivatives across asset risk-weights.[18]

The L schedule from the FR-Y14Q contains 18 sub-schedules and provides unique information about the derivative profile by counterparty as well as aggregated across all counterparties of each reporting bank. We use sub-schedules L1.a, L1.b, L1.c, L1.d, and L1.e for most of the analysis. Sub-schedule L1.e provides information at the aggregate level distinguishing between exposures where the counterparty is a CCP and not.[19] Possible counterparties include (but are not limited to) other Bank Holding Companies (BHCs), other financial institutions (e.g., insurance companies, hedge funds, nonbank financial institutions), sovereigns, non-financial corporations, and central counterparties. Designated central clearing counterparty (CCP) exposures include both cleared over-the-counter (OTC) derivatives and exchange traded derivatives. All counterparties have a unique identifier and reporting banks provide the name and type of the counterparty which allows as to track relationships over time, with information on the industry code (six digit NAICS code), the country of domicile of the counterparty, an internal rating, and (when available) the external rating of the counterparty.[20] We focus primarily on the network of U.S. counterparties. We document the changes in exposures using Gross Credit Exposure (Gross CE). Gross CE is pre-collateral exposure after bilateral counterparty netting. Sometimes referred to as the replacement cost or current credit exposure, Gross CE is the fair value of a derivative contract when that fair value is positive. Gross CE is zero when the fair value is

[17] This is not an important restriction since derivative activity is highly concentrated. Four banks with the most derivative activity (J.P. Morgan Chase Bank, Bank of America, Citibank, and Goldman Sachs, which are included in our sample) hold 87.4 percent of all bank derivatives (by notional value).

[18] When using this split the report uses credit equivalent which adds current credit exposure (sometimes refereed to as the replacement cost) plus the potential future exposure over the remaining life of the derivative contract. The current credit exposure is (1) the fair value of the contract when the fair value is positive and (2) zero when the fair value is negative or zero. Bilateral netting agreement between the reporting bank and a counterparty may ne taken into consideration.

[19] Required reporting of all Central Counterparties started in 2015. Sub-schedules L1.a-d provide a significant share of the aggregate exposure. We discuss this further below.

[20] The reporting requirements by type of counterparty changes over time as the data requirements evolved during the last decade.

negative or zero.[21]

Combining these two key sources we provide a comprehensive picture of derivate activity for most banks in the U.S. and describe the network of exposures for the most relevant players (i.e., those that we defined as core banks). As our theory suggests, the core is where cycles reside and the systemic risk originates. We also focus on the links between the core and periphery and central counterparties.

3.3 Aggregate patterns

The regulatory changes that we described above lead to an increase in aggregate central clearing activity. This, however, did not translated in an increase in the fraction of central cleared derivatives for core banks. More specifically, we compute the share of derivatives that are centrally cleared $s^c_{b,t}$ for bank b in period t which following the notation in our model can be written as follows

$$s^c_{b,t} = \frac{E_{bc,t}}{E_{bc,t} + \sum_{j \neq c} E_{bj,t}}, \tag{4}$$

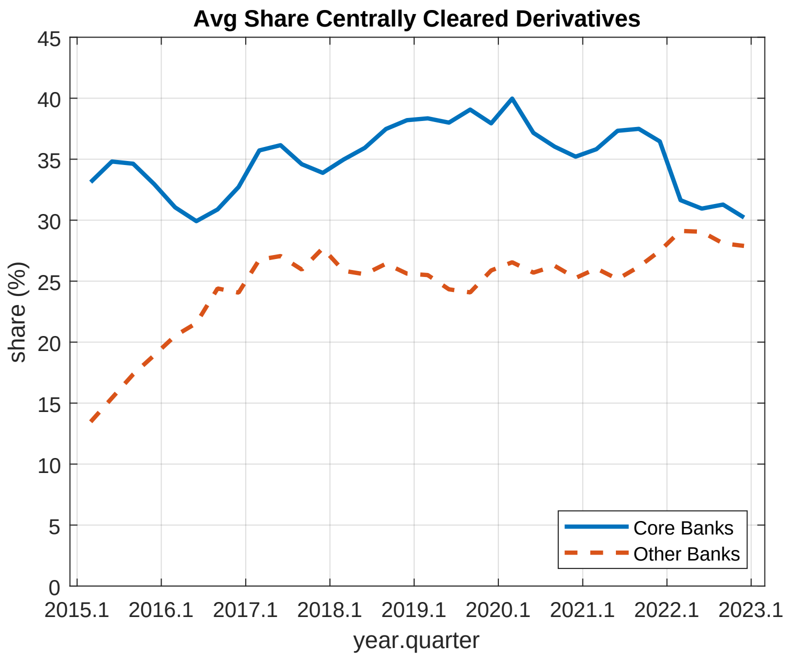
where $E_{bc,t}$ refers to total exposure to central counterparties (total derivatives that are centrally cleared) and $\sum_{j \neq c} E_{bj,t}$ represents total derivatives that are not centrally cleared (i.e., transacted over-the-counter with counterparties other than central counterparties c). We measure $E_{bj,t}$ using credit equivalents in the case of the FR-Y9C and Gross CE or Net CE in the case of FR-Y14Q. With the bank level estimates at hand, we then compute the asset weighted average within bank group (core and non-core) $\overline{s}^{c,K}_t = \sum_{b \in K} s^c_{b,t} \omega^K_{b,t}$ where as before K denotes the set of core banks and $\omega^K_{b,t}$ is the share of assets of bank $b \in K$ in period t. We also compute $\overline{s}^{c,P}_t$ for banks not in the core (where P as in the model denotes peripheral banks). Figure 10 presents $\overline{s}^{c,K}_t$ and $\overline{s}^{c,P}_t$ using data from FR-Y9C. Data on $E_{bc,t}$ and $\sum_{j \neq c} E_{bj,t}$ from this source is only available since 2015 which we identify with the post-reform period.[22] Figure 10 shows that $\overline{s}^{c,K}_t$ (i.e., the average share of the credit equivalent that is centrally cleared) has remained relatively constant for core banks since 2015 (i.e., banks that report consistently counterparty risk in the FR-Y14Q). We observe an increase from 33% to 38% between 2015 to 2018 followed by a declined to 36.6% at the end of 2021. There seems to be a significant increase for other banks ($\overline{s}^{c,P}_t$) for which the share of total exposure to CCPs increases between 19% in 2015 to 28% at the end of 2022.

[21] Other available measure of exposure is Net Credit Exposure (Net CE). Net CE corresponds to Gross CE less the value of collateral posted by the counterparty to secure those trades. Only collateral that was actually exchanged is incorporated in the Net CE reporting. This measure however is subject to assumptions about the value of collateral and how that value is reported. In addition, it is not fully consistent with how exposures are accounted for in our model. For these reasons most of our analysis is based on Gross CE but we also discuss how our the empirical results are affected by different measures of exposure below.

[22] As we described before, except for margin requirements for OTC derivatives, other dimensions of the reform of OTC markets (central clearing, reporting, capital requirements) were in place by 2015 in the US.

This figure suggests that during the post-reform period there is still significant activity that is traded OTC among core banks and that the incentives to centrally cleared were stronger for banks outside the largest six (i.e., core banks). That is, at the aggregate level the dynamics in the banking sector appear to be consistent with decoupled clearing (see Proposition 5). In that sense, regulations induced an increase in central clearing but the increase is mostly explained by banks outside the core which hints into regulations being somewhat ineffective at reducing cycles that involve the largest banks in the system. With the counterparty data at hand we will describe the evolution of these cycles and show that this is in fact the case in the next section.

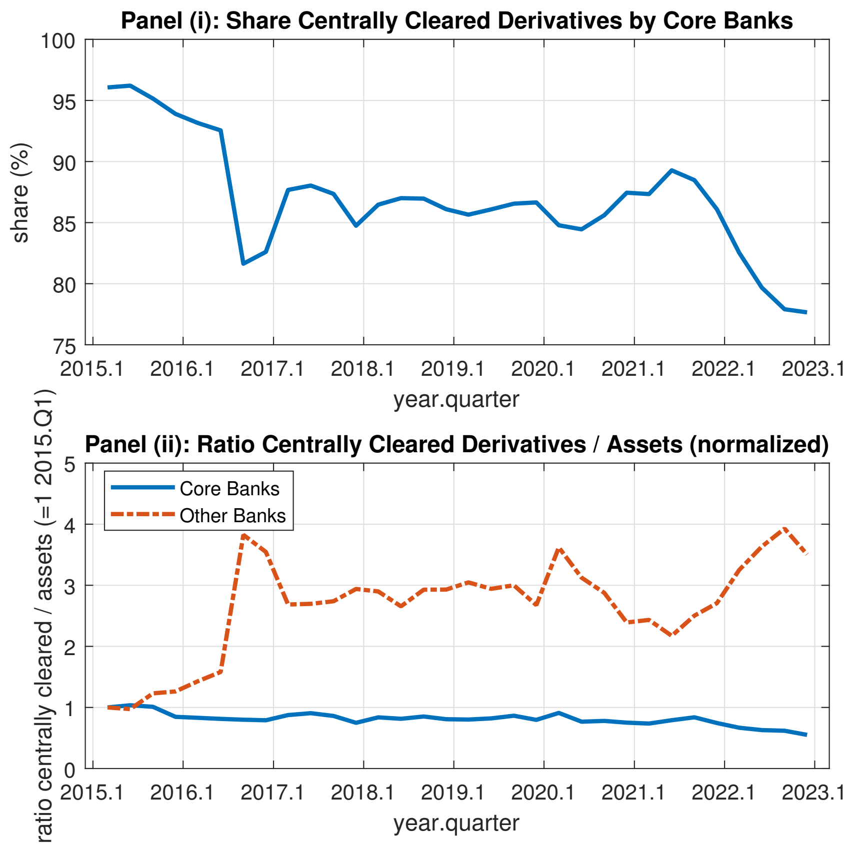
Figure 10: Fraction of Centrally Cleared Derivatives
(core $\overline{s}_t^{cc,\mathcal{C}}$ and non-core banks $\overline{s}_t^{cc,\mathcal{NC}}$)



Note: "CCP" corresponds to Central Counterparty (centrally cleared derivatives). Core banks refer to banks that report counterparty risk in our Fr-Y14Q data. Other Banks corresponds to all other reporting banks. Avg Share corresponds to the asset weighted average of the bank specific CCP share. Source: Consolidated Financial Statements for BHCs (Y-9C - HC-R)

We continue the analysis of how central clearing evolved in the banking sector and compute two additional measures of central clearing activity among core and other banks. First, we compute the share of all centrally cleared derivatives that are accounted for by core banks' centrally cleared derivatives. That is, we estimate $\frac{\sum_{b\in K} E_{bc,t}}{\sum_{b\in K} E_{bc,t}+\sum_{b\in P} E_{bc,t}}$ and present this ratio (in percent) in Panel (i) of Figure 11. Second, as growth dynamics during this period across the bank size distribution differs, we compute $\frac{\sum_{b\in K} E_{bc,t}}{\sum_{b\in K} A_{b,t}}$ and $\frac{\sum_{b\in P} E_{bc,t}}{\sum_{b\in P} A_{b,t}}$ where $A_{b,t}$ represents total assets for bank b in period t. Panel (ii) in Figure 11 displays the evolution of this ratio over time (normalized to 1 in 2015.Q1) one more time using data from the FR-Y9C. The figure makes evident two facts: first, in the US, core banks account for the lion share of centrally cleared derivatives in the banking sector with close to 85 percent, on average (Panel (i)). Second, this share has declined in the recent period going from over 95 percent in 2015 to just above 75 percent by the end of 2022 (a decline of 20 percentage points). That is, the importance of other smaller banks in markets for cleared derivatives has increased (Panel (i)). The growth of central clearing for banks outside the core has outpace the growth of assets in this portion of the banking sector. The decline for core banks in central clearing relative to the growth of assets is significant as it declines by almost 50% (Panel (ii)).

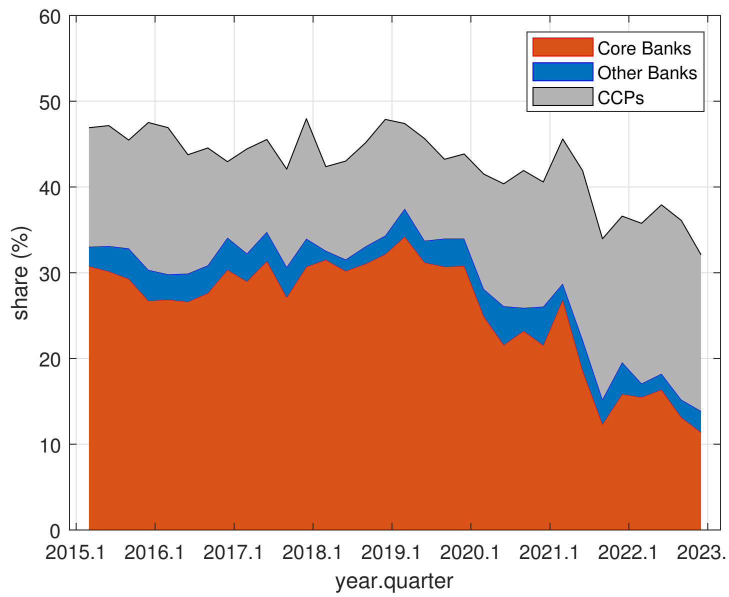
Figure 11: Share of Total Centrally Cleared by Core Banks



Note: "CCP" corresponds to Central Counterparty (centrally cleared derivatives) Source: Consolidated Financial Statements for BHCs (FR-Y9C - HC-R)

In our next step, we make use of our confidential data as it contains unique information about the derivative profile by counterparty and aggregated across all counterparties of each reporting bank. We classify counterparties based on information provided by the supervision group at the Federal Reserve Bank of New York which takes into account among other things the ownership structure of financial institutions. Focusing on counterparties in the U.S., we can identify core banks, other banks, central counterparties (CCPs), non-financial corporations, government entities, non-financial corporations, and other institutions (e.g., financial guarantors, pension funds, special purpose vehicles). Using this information, quarter by quarter, we compute the exposure of each reporting bank to each counterparty type by aggregating information at the individual counterparty level and taking ratios to overall exposures.[23] We use Gross CE as our measure of exposure (pre-collateral exposure after bilateral counterparty netting). This measure presents a clear picture of the real exposure of each of the core banks to their counterparties. Figure 12 displays the (asset-weighted) average of Gross CE by counterparty type. We focus on the exposure of core banks to core banks, other banks, and CCPs as they are the most salient groups by exposure in the financial sector and are the focus of our model.[24]

Figure 12: Counterparty Exposure Gross CE by counterparty type (core banks)



Note: Asset weighted average of bank level Gross credit exposure by counterparty type (core banks to U.S. counterparties). Data from core banks with consistent time series. "CCPs" corresponds to Central Counterparty, , "Core" corresponds to the reporting banks, "Other Banks" to other banks not in the "Core" category. Source: Consolidated Financial Statements (FR-Y9C) and FR-Y14Q (schedule L)

Figure 12 shows that exposure to core banks is significant with the average exposure of core banks to other core banks being 25.6%. Core to core exposure is the remains the largest exposure by counterparty type until 2021 Q1. It is relatively flat at approximately 30% between 2015 and 2021.Q1 and over 16% during 2021 and 2022.[25] That is, the exposure "core to core" remained a significant factor in explaining counterparty risk since 2015 and throughout the pandemic and, while it has declined since 2021.Q2, still remains elevated.[26] A key insight from our model is that

[23]We complement sub-schedules L1a,L1b,L1c, and L1d with sub-schedule L1e. In 2020.Q1 there are significant reporting changes as sub-schedules L1.c and L1.d stop being reporting making the use of L1.e for the exposure to CCPs crucial. Figure A.1 presents a comparison between the aggregate levels reported in sub-schedule L1e and the aggregate values from sub-schedules L1a-d.

[24]Figure A.2 in the Appendix presents exposure to the full set of U.S. counterparties by type.

[25]Reporting restrictions prevent us from disclosing the evolution of exposures at the bank level, but we can mention that not one bank is the main driver of the figure, in the sense that, all banks in our sample present similar patterns. Figure A.4 in the Appendix presents the pattern when using Net CE as a measure of exposure. That figure suggests that core banks are intensive in the use of collateral, and that shows as increase in the relative importance of CCPs exposure compared to the case of exposure measured using Gross CE.

[26]Figure A.2 in the Appendix shows that the decline in exposure to core banks post 2021.Q1 is associated

the impact on clearing on coordination failures depends on details beyond the amount of clearing. In the sections that follow, we show that the decline in core to core exposure has not affected key properties of the cycles generated by derivative exposures within the core. Of particular relevance is the fact that core banks correspond to only 6 institutions. The average share of the top counterparty among core banks (using Gross CE as the measure of exposure) was 54.9% in 2021.Q4. The average share of the top counterparty by type was 38.8%, 70.5%, 41.7%, and 5.5% for other banks, CCPs, government entities, and non-financial corporates, respectively, also in 2021.Q4. Figure 12 also makes evident that while regulatory changes induced an increase in the exposure to CCPs, the increase is not very dramatic as the average exposure of core banks to CCPs is 12.4% between 2015 and 2019 and 18.7% between 2021 and 2022.[27] This one more time is line with the decoupled clearing case discussed in Proposition 5.

3.4 Mapping the Regulatory Environment to the Model

The changes in regulations can be represented as shifts in the relative cost (δ) of clearing contracts through CCPs versus OTC channels. By analyzing observed preferences, the documented changes in clearing behavior provide insights into how regulations have affected these costs.

Empirically, we find that the core's share of centrally cleared derivatives has remained relatively stable relative to overall derivative activity but has declined relative to total assets (Figures 10 and 11). This suggests that the regulatory-induced increase in clearing incentives primarily benefited non-core banks, non-financial corporations, or non-banks, as evidenced by the increased exposure of core banks to institutions other than CCPs in the recent period. Among the possibilities highlighted in Proposition 5, the data points towards the case of $\delta_{PK} < 0 < \delta_{KP}, \delta_{KK}$, where the periphery clears exposures from the core, but the core does not clear internally.

The two most prominent regulatory changes can be summarized as increased CCP transparency relative to OTC contracts and increased collateral costs for OTC relative to CCP contracts. Considering exposures as insurance contracts between banks, the exposed party (insurance buyer) may signal weakness, increasing funding costs. Thus, transparency might have increased δ (the relative cost of CCP clearing). Conversely, collateral regulations, requiring the exposed party to hold regulatory capital proportional to risk, might have decreased δ.

The data suggests a bank-specific ranking based on their varying valuations of opacity and collateral. Core banks, facing higher scrutiny but less constrained by capital requirements due to

with an increase in exposure to non-financial corporations as well as an increase in exposure to nonbank financial institutions. In 2022.Q4 non-financial corporations and nonbank financial institutions account for 40.6% and 9% of total Gross CE exposures (among U.S. counterparties). Figure A.3 presents the average exposure of core banks to all counterparties (U.S. and foreign) and shows that there is a similar increase in exposure to non-financial corporates and nonbank financial institutions with a somewhat larger increase of nonbank financial institutions.

[27] Figure A.4 in the Appendix shows that when using Net CE as the measure of exposure (billateral netted exposure net of collateral) the increase in exposure to CCPs is larger as collateral use appears to be larger for other counterparties.

abundant regulatory capital, are likely less incentivized to clear contracts compared to periphery banks. This implies higher transparency costs and lower collateral benefits for core banks. Thus, the system may have transitioned from a state where $0 < \delta_{PK}, \delta_{KP}, \delta_{KK}$ to one where $\delta_{PK} < 0 < \delta_{KP}, \delta_{KK}$.[28]

Interestingly, the observed change in clearing is consistent with an increase in systemic risk (Φ). The potential unintended consequence of regulation leading to decoupled clearing, where cycles persist but are magnified by larger internal fragility, highlights the need for regulations that incentivize core clearing, not periphery clearing.

Examples of such regulation include designing clearing mechanisms less reliant on specific contract information, alleviating core banks' concerns about exposing themselves and their information to the CCP. A key consideration is incentivizing banks to clear proportionally to their pre-existing clearing rates. This avoids unintended consequences from asymmetrically changing extensive margins while reducing the intensive margins of OTC exposures and mitigating coordination failures.

3.5 Coordination Failures Regions

The model prompts us to examine not only the level of central clearing relative to OTC derivatives but also bilateral exposures. Before delving into confidential counterparty data, we utilize public data to infer whether banks operate within a parameter space conducive to coordination failures. Recall that our model predicts a coordination failure region defined by $\boldsymbol{\phi}' < \boldsymbol{\alpha} < \boldsymbol{\phi}$. We first analyze the evolution of $\boldsymbol{\phi}'$ and $\boldsymbol{\phi}$ over time. Specifically, we interpret ϕ_i' as a measure of fundamental economic risk independent of coordination failures, $\phi_i - \phi_i'$ as a measure of coordination failure risk, and ϕ_i as a measure of combined systemic risk.

We do not observe shocks so we rely on observed $\tilde{A}_i$ to reflect A_i in our constructed measures. In particular, we estimate ϕ_i for each bank i as

$$\hat{\phi}_i \equiv (L_i + D_i)\tilde{A}_i^{-1} \tag{5}$$

where $\tilde{A}_i$ corresponds to (on-balance-sheet) assets, L_i to total (on-balance-sheet) liabilities, and D_i is measured using the schedule HC-L in the FR-Y9C that captures off-balance sheet debt positions using "Credit Derivatives, Gross negative fair value" which represents a measure of the exposure the bank i posses to its counterparties.[29] This is only reported by large institutions.

[28] We endogenize costs, exposures, and the intensive margin of clearing in an earlier version of the paper, available upon request. In this paper, we take costs and exposures as given and study the extensive margins of clearing. The resulting insights are nearly identical.

[29] See Appendix for a description of variables used in the analysis. This measure is consistent with the measure used by the OCC in their Quarterly Report on Bank Trading and Derivatives Activities to estimate credit exposure in derivative contracts. The OCC report states "The total of all contracts with negative value (i.e., derivative payables) to the bank is the gross negative fair value (GNFV) and represents a measurement of the

We can also measure ϕ' for each bank i as

$$\hat{\phi}_i' \equiv (L_i + D_i - E_i)\tilde{A}_i^{-1} \tag{6}$$

where E_i comes also from schedule HC-L "Credit Derivatives, Gross positive fair value" and represents the exposure of bank i to all other counterparties.[30]

The data allows us to look at the evolution of $\hat{\phi}_i$ and $\hat{\phi}_i'$ since the early 2000s. We can measure the evolution of the region that allows coordination failures in the run up to the great financial crisis in 2008 as well as the most recent period. Panels (*i*) and (*iii*) in Figure 13 present the full time series and panels (*ii*) and (*iv*) zooms in on the most recent period. Panel (*i*) and (*ii*) present the asset-weighted average of $\hat{\phi}_i$ and $\hat{\phi}_i'$ among core banks. Panels (*ii*) and (*iv*) present the components as described in equations (5) and (6). As before, we define the "post-reform" period as the period that starts in 2015.Q1 (the focus of Panels (*ii*) and (*iv*)). The vertical dotted lines in Panels (*i*) and (*iii*) enclose a period that we defined as a transition period since reforms were already announced but were in the process of being implemented.

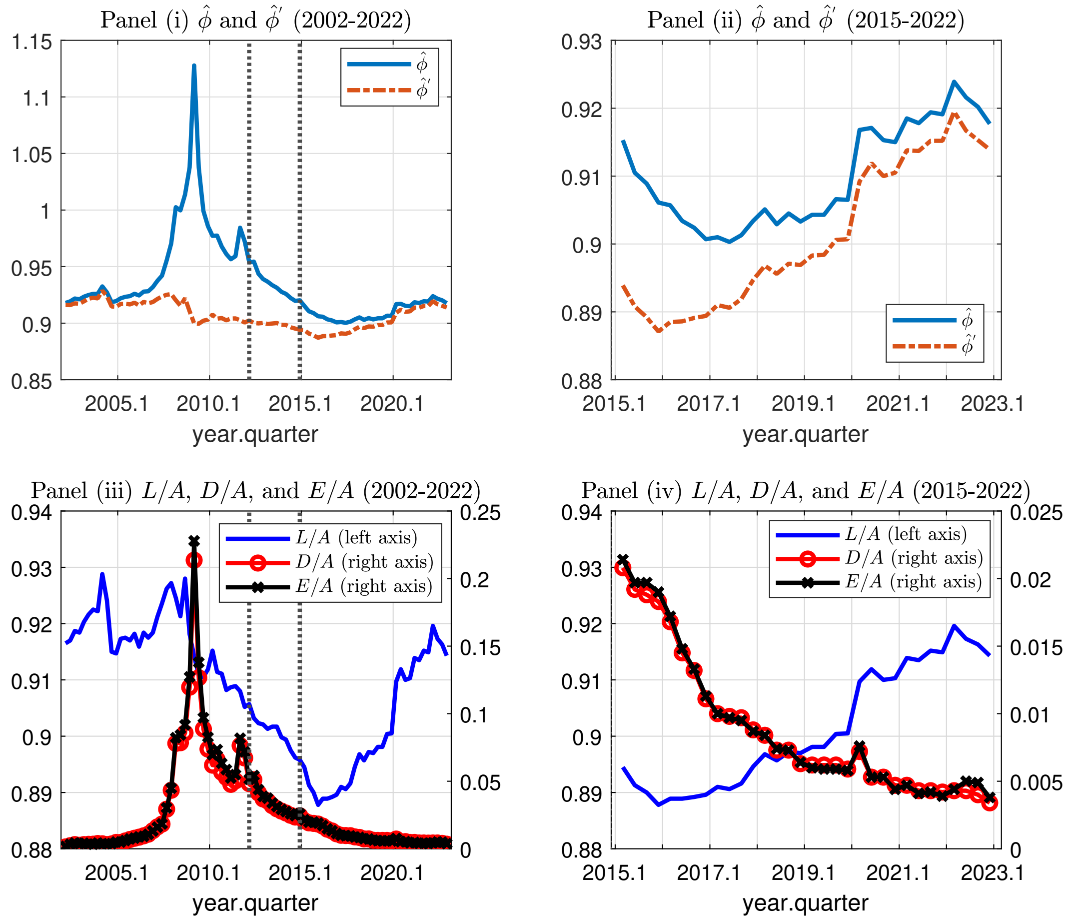
The observed patterns are striking. Panel (i) reveals a dramatic increase in the (average) region enabling coordination failures in the lead-up to the crisis, without a corresponding rise in fundamental risk (measured by weighted-average $\hat{\phi}_i'$). This indicates that the majority of the increase in systemic risk (ϕ_i) can be attributed to changes in the difference between average ϕ_i and ϕ_i'.

A closer examination of the components underlying ϕ_i and ϕ_i' in Panel (iii) shows a significant rise in interbank assets and liabilities in the pre-crisis period. This supports the notion that the unraveling of complex interbank activity, which would otherwise net out to zero, contributed to the 2008 financial crisis. While L/A remains stable during this period and only declines after the initial shock and subsequent capital regulation changes, Panel (iii) also reveals that the difference between D/A and E/A is generally small relative to the scale of L/A. Thus, under normal conditions, $A - L + E - D$ is positive and sufficiently large. However, even though $D/A - E/A \approx 0$, both D/A and E/A grow significantly. During periods of interbank distrust, potentially triggered by a decline in collateral value, the fulfillment of E/A can drop rapidly, leading to an imbalance where $A - L - D \ll 0$, causing non-payments and justifying the loss in E/A. While A might be large enough to cover L, the disproportionate growth of D/A creates vulnerability. This is evident in Panel (i), as the weighted average $\hat{\phi}_i$ increases significantly during the crisis while average $\hat{\phi}_i'$ remains stable or slightly declines.

exposure the bank poses to its counterparties." A drawback of this measure is that it only includes exposures from OTC derivative transactions (see OCC report).

[30] According to the OCC "contracts on which a bank would lose value if the counterparty to a contract defaulted. The total of all contracts with positive value (i.e., derivative receivables) to the bank is the gross positive fair value (GPFV) and represents an initial measurement of credit exposure." Note that $D_i - E_i$ does not capture any bilateral credit agreement between counterparties.

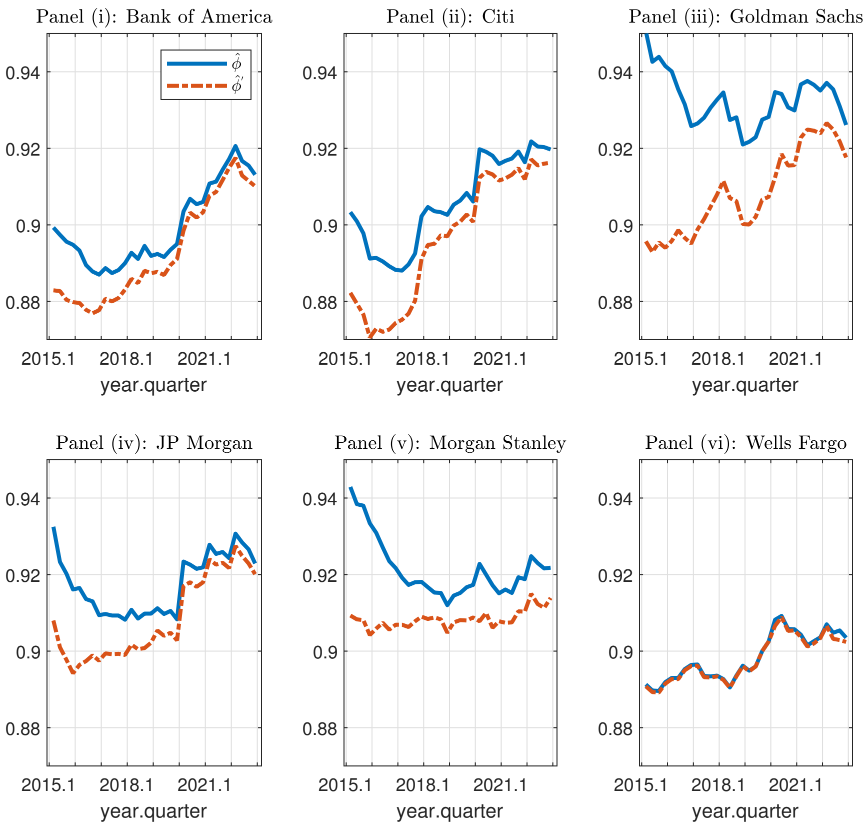
Figure 13: Coordination Failure Region and Determinants (average)



Note: The figure presents the asset-weighted average of $\hat{\phi}_i$ and $\hat{\phi}_i'$ as defined in equations (5) and (6). Data for Goldman Sachs and Morgan Stanley only start after 2009 (when they became commercial banks). L/A corresponds to liabilities over assets, D/A corresponds to total (interbank) debt over assets. Dotted vertical lines correspond to a period of transition after reforms were announced but not yet fully implemented. We define the post-reform period that starts in 2015.Q1 Source: Consolidated Financial Statements (FR-Y9C)

Therefore, as Figure 13 shows, the pre-reform period, including the financial crisis, serves as a benchmark or indicator of the OTC system approaching high systemic risk, validating our model's measure. Panels (i) and (ii) further demonstrate that the region allowing for coordination failures begins to shrink after its 2008 peak but remains positive, suggesting that a systemic crisis due to coordination failures remains feasible according to our model's predictions. That is the data suggests that post reform it is less likely that coordination failures get triggered inside the core. However, the region where coordination failures are allowed does not shrink enough to eliminate cycles completely. In addition, since we also find evidence of decoupling (as defined in Theorem 5), we find that if coordination failures get triggered, they might spread and cause more damage than in the past. The effects of a crisis will get amplified via the CCP.

Figure 14: Coordination Failure Region (ϕ and $\hat{\phi}'$) by bank - Post Reform



Note: Figure shows $\hat{\phi}$ (see equation 5) and $\hat{\phi}'$ (see equation 6) by bank.
Source: Consolidated Financial Statements for BHCs (FR-Y9C)

We explore whether bank heterogeneity plays a role in the described dynamics. Figure 14 plots ϕ_i and ϕ_i' for each bank over time zooming in on the recent period.[31] Coming out from the financial crisis, the region of coordination failures declines in size in the post-GFC period, but remains non-negligible for most banks (the exception is Wells Fargo - Panel (vi)). That is, the regulatory changes do not seem to affect in a fundamental way the possibility of coordination failures that can suddenly expand as during the great financial crisis. In fact, Figure 14 Panels (ii)-(v) suggest that there was an increase in systemic risk during the early periods of the pandemic. For example, at the peak of the pandemic the gap between $\hat{\phi}_i$ and $\hat{\phi}_i'$ increased by 11.4% and 103.1% for Citi and Morgan Stanley, respectively, relative to the 2018-2019 average. Consistent with Figure 13, Figure 14 also shows that exposures are growing, increasing the fundamental risk whereas coordination failure risk remains stable but it has also grown during the post-reform period.

Theories of Systemic Risk. These results contribute to the debate between the "popcorn" and "domino" theories of financial crises, as detailed in Erol and Vohra (2022). The popcorn

[31]Figure A.5 in the Appendix presents the full time series. Consistent with the average presented in Figure 13, data for each bank reveals that the coordination failure region (ϕ_i', ϕ_i) expands dramatically in the build up towards the financial crises in 2008.

theory attributes crises primarily to common exposures to external factors, while the domino theory emphasizes cascading failures due to interbank exposures.

Our model accommodates both theories by demonstrating how common exposures can erode confidence and trigger cascading failures. We introduce a theory of an endogenous common shock, the coordination failure, arising from the dynamic interaction between exogenous shocks and interconnectedness. This can be likened to a "dome" theory. The hemispherical structure of a dome balances itself by distributing weight in all directions, providing earthquake resistance without external support. However, when the earthquake's magnitude exceeds a threshold, the self-supporting system collapses suddenly and completely. The financial network of derivative exposures represents the structural integrity and weight of the dome.

Our findings indicate that, in the context of derivatives and the financial crises of 2008, the popcorn or domino theories alone (changes in ϕ') are less significant contributors to systemic risk (changes in ϕ) compared to our dome theory represented by coordination failures (changes in $\phi - \phi'$). This highlights the importance of considering both external shocks and the interconnectedness in combination in understanding and mitigating systemic risk.

4 The Anatomy of Cycles within the Core

Our theory emphasizes that cyclic exposures are a prerequisite for coordination failures. In addition to their necessity, the properties of cycles significantly influence the prevalence of coordination failures and systemic risk. Access to confidential regulatory data allows us to examine key characteristics of cycles among major players.

The necessity of cycles highlights the possibility of self-fulfilling cyclic payment failures. Each cycle can be a source of such failures under certain conditions. This concept can be mapped to our model by defining weaker notions of coordination failures, such as a (weak) coordination failure defined as the self-fulfilling failure of a specific subset of banks. The possibility of such a failure would necessitate the presence of a cycle-rooted tree within the subnetwork of the subset of banks (exposures with banks outside the subset would be treated as external assets and liabilities). This suggests that each cycle can trigger a cyclic payment failure among the banks within it under specific shock combinations. This failure, initiated on the cycle, can then propagate outwards through acyclic exposures, as indicated by the cycle-rooted tree in Figure 2. The extent of propagation depends on the reach of the"branches" of this tree, potentially escalating a cyclic failure into a systemic event. In a sense, cycles within central network locations (like the core) constitute systemically important groups of banks, rather than unstructured groups of systemically important individual banks.

Building on this insight, we propose and explore notions of network complexity and bank centrality, measured using our confidential dataset. Network complexity is assessed based on the prevalence of cycles (extensive margin) and the exposures within these cycles (intensive margin). Bank centrality is determined by the bank's presence within cycles, which can increase the cycle's, and hence the system's, exposure to that particular bank.

These findings lead to network-prudential policy suggestions. Complexity serves as a measure of systemic vulnerability to various manifestations of non-fundamental risk. However, complexity does not pinpoint the origin or propagation of problems. Centrality, on the other hand, identifies vulnerable locations within a complex network. If the market perceives trouble at a high-centrality bank, numerous subsets of banks may lose confidence in their counterparties due to inductive reasoning about potential cyclic failures. Thus, perceived problems with high-centrality banks can trigger systemic events.

In the following sections, we identify and describe cycles within the core of the U.S. banking system over time, then propose and explore various notions of complexity and centrality.

4.1 Identifying Cycles

We identify cycles using data collected for Stress Testing purposes (FR-Y14Q - Schedule L). The measure of exposure of one bank to another we continue to use is Gross CE as it aligns with the definition of credit equivalent (CE) in the call report data that we used before and it is immune to fluctuations or assumptions about the value of collateral.[32] As we described before the banks for which we can construct consistent time series are Citi, Bank of America, Wells Fargo, Morgan Stanley, Goldman Sachs, and JP Morgan. Disclosure limitations prevent us from providing the name of the banks so we randomly assign a number between 1 and 6 when presenting the cycles within the core.

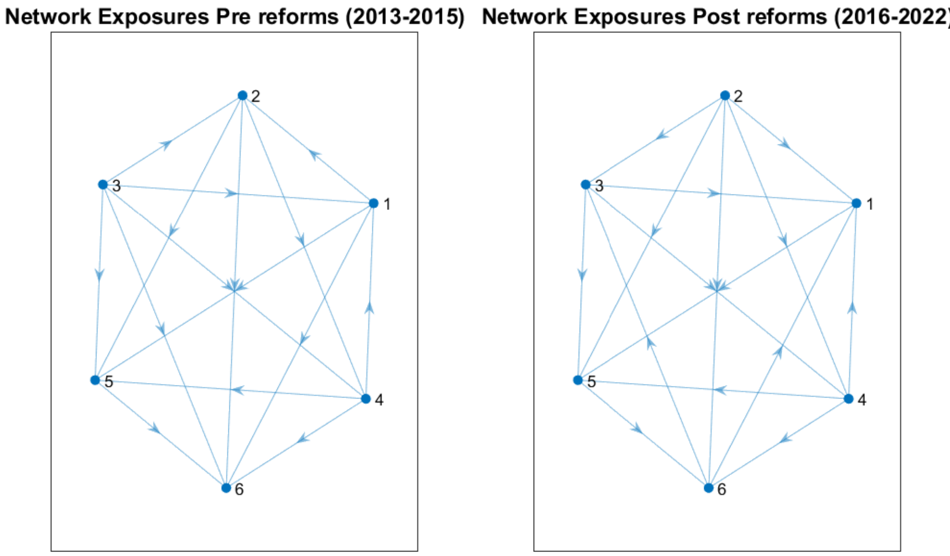
Figure 15 presents the direction of exposures between "core" banks before and after regulatory changes.[33] Arrows going from bank "B" to bank "A" corresponds to how exposed is bank "A" to bank "B" (i.e., the pre-collateral fair value (when positive) of the netted exposure of bank "A" to bank "B").[34] We observe some fluctuations across time but we do not observe fundamental changes in how connected core banks are among themselves. It is immediately clear from this comparison that the system within the core was before regulation completely integrated in terms of exposures and this remained the case after regulation. We observe that the direction of the exposure reverses in 4 out of 15 pairs but the fundamental links are similar across time periods. Not all these exposures, however, are part of a cycle necessary, as we explain next.

[32] The OCC uses GCE as its primary metric to evaluate credit risk in bank derivative activities in its Quarterly Derivatives Report. The measure (called Net Current Credit Exposure) is available at the level of total derivatives from the Call Reports schedule RC-R.

[33] The figure shows only the direction of exposures as the data clearance process prevented us from showing the values or intensities. We construct the time series average for each exposure pairs and present the network based on these average exposures pre and post reforms. Below, we describe specific quarters.

[34] This is effectively the potential market value of losses in the event bank "B" defaults on commitments to bank "A".

Figure 15: Counterparty Exposure (GCE) ("core") Average Pre Reform (2013-2015) and Post Reform (2016-2022)



Note: Figures shows exposures across core banks (numbered 1-6) of GCE (Gross Credit Exposure). We construct the time series average for each exposure pair conditional on years for pre and post-reform and present the network based on these average exposures for each period. Direction of arrows $j \to i$ indicates bank i is exposed to j. Source: BHCs FR Y14Q Schedule L

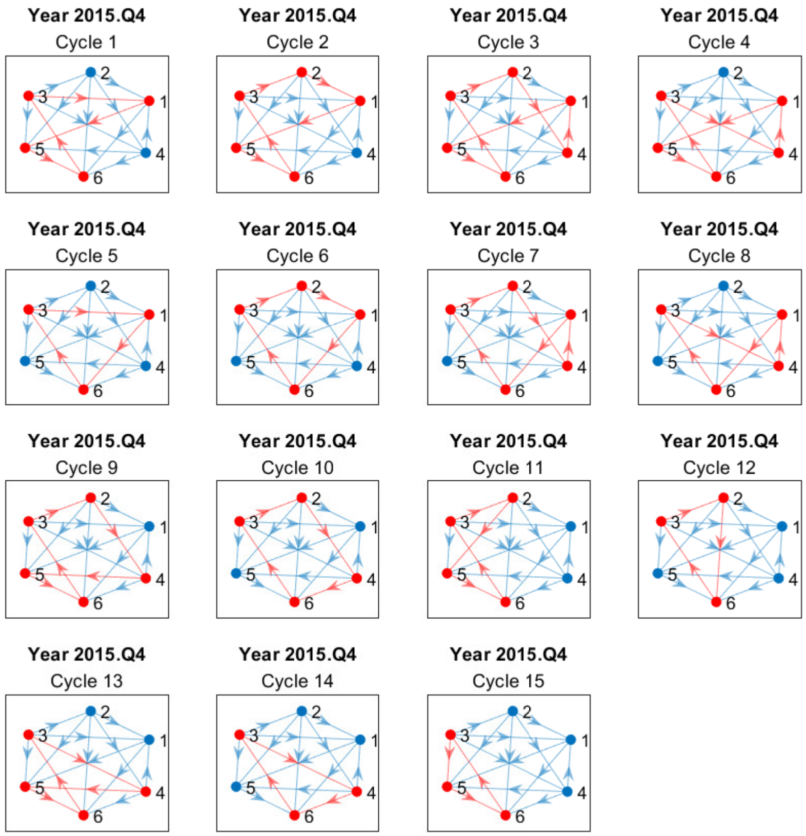
We explore further the linkages between core banks paying particular attention to cycles that derived from exposures within the core. We also evaluate whether these cycles have changed in the post-reform period. Figure 16 displays all the existing cycles in 2015.Q4 (highlighted in red on top of the base network).[35] There are 15 cycles and the average number of nodes in each cycles is approximately 4 banks. Each cycle makes up the root of a directed tree of exposures along the lines of Figure 2. This means, there are 15 different cycles that could trigger coordination failures and cyclic self-fulfilling losses, which can then propagate to other banks. Figure 16 summarizes all the different paths a lack of payment can flow through the system in a self-confirming fashion.

Figure 17 depicts all the cycles that existed four years later, during 2019.Q4 (the quarter prior to the beginning of the pandemic). In 2019.Q4. there were 6 cycles, also with an average number of nodes in each cycle of approximately 4 banks. In this quarter, for instance, Bank 2 is not exposed to any other bank (this can be seen as there are no arrows coming into bank 2).[36] That is, bank 2 is neither a part of a cycle nor exposed indirectly to a cycle along the lines of Figure 2. This observation is relevant because it implies that in 2019.Q4, a complete coordination failure involving a self-fulfilling default of *all* banks was not possible. However,

[35]As in the previous picture, disclosure limitations prevent us from showing the intensity of the exposures between banks.

[36]Figure A.6 in the Appendix presents the cycles for the most recent quarter in our sample 2022.Q4 with no additional significant insights. In 2022.Q4 there are 7 cycles with bank 2 being part of all of them and bank 6 becoming the bank that is not exposed to other banks.

Figure 16: Cycles Banking Network 2015.Q4

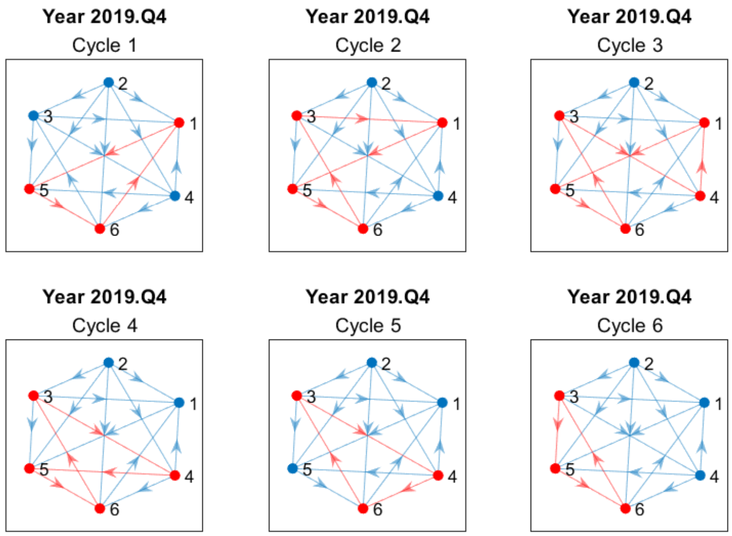


Note: Each panel shows exposures across core banks (numbered 1-6) of GCE (Gross Credit Exposure). Links highlighted in each panel correspond to a given cycle. Direction of arrows $j \to i$ indicates bank i is exposed to j. Source: BHCs FR Y14Q Schedule L

there is the possibility of a coordination failure involving five of them. We could identify the probability that a specific subset of banks default by extending our theory to the subnetwork of exposures among the specific subset of banks. Still, as we will see, it is quite informative that in most periods all banks seem to be connected to at least one cycle within the core providing additional evidence in favor of the case where $\delta_{KK} > 0$.

Using the cycles depicted in Figure 17 for 2019.Q4 as an example, it is also relevant to note that while Bank 2 is not a node in any cycle, this does not immediately imply that Bank 2 is not relevant from a systemic risk perspective. All other banks are exposed to Bank 2, which may then be a potential source of aggregate risk in and of itself. The idiosyncratic risks of Bank 2 becomes aggregate risks of the other 5 banks, contributing to their coordination failure region. Therefore, a weaker, yet strong enough notion of coordination failures can persist. We explore these in the ideas next.

Figure 17: Cycles Banking Network 2019.Q4



Note: Each panel shows exposures across core banks (numbered 1-6) of GCE (Gross Credit Exposure). Links highlighted in each panel correspond to a given cycle. Direction of arrows $j \rightarrow i$ indicates bank i is exposed to j. Source: BHCs FR Y14Q Schedule L

4.2 Complexity

While a broadly applicable measure of cycle-related complexity does not exist, certain indicators can inform us systemic risk. Our measure accounts for the number of cycles in the network, weighted appropriately by key exposures to reflect their significance.[37]

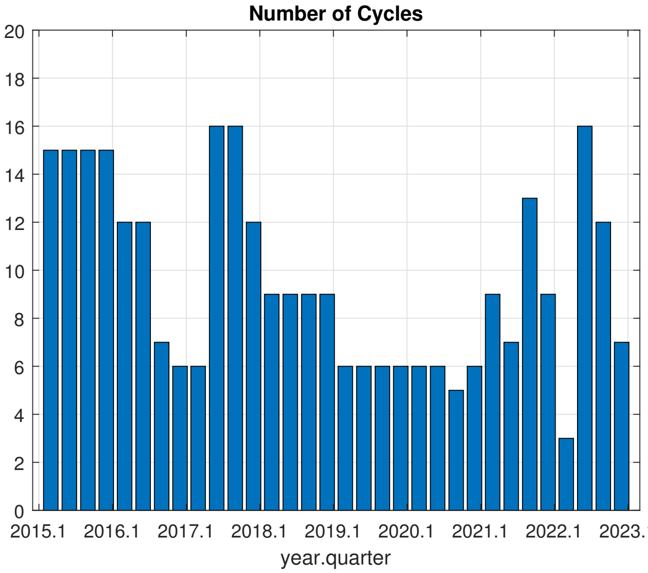
Number of cycles: Figure 18 presents the number of cycles over time. Given that our theoretical framework allows for arbitrary correlations in shocks, each cycle can potentially be triggered under specific shock combinations affecting its members and their exposures.

Overall, this measure of complexity suggests a slight decline over time, as the number of cycles fluctuates between 12 and 14 in the early periods but narrows to a range of 6 to 8 between 2018 and 2021. However, recent volatility is evident, with the number of cycles ranging between 2 and 16 during 2022. This increased volatility in the number of cycles indicates a potential rise in network complexity and warrants further investigation.

Our theory refines this measure of complexity. It's not just the number of cycles that matters, but also the magnitude of exposures within them. A cyclic failure occurs when the non-payment of a certain amount by one bank to another leads to a chain reaction of defaults within the cycle. This self-fulfilling loss cannot exceed any bilateral obligation in the cycle. For example, if A pays \$$x$ less than its original obligation to B, then possibly B is \$$x$ short pays \$$x$ less than its obligation to C, then possibly C is \$$x$ short and pays \$$x$ less than its obligation to A, so A is

[37] In addition to the weighted number of cycles, Figure A.7 in the appendix presents measures based on the number of nodes across the observed cycles. The number of nodes on a cycle can reflect the difficulty of trust and coordination in avoiding cyclic losses, as well as affect the extent and reach of cyclic failures.

Figure 18: Number of Cycles



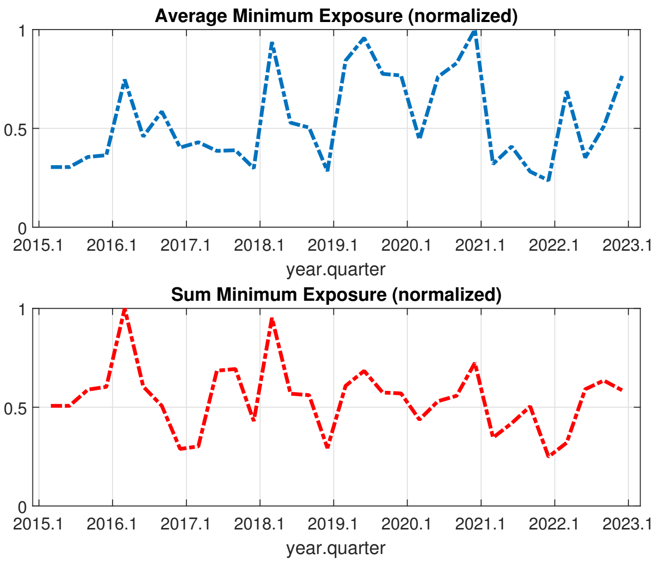
Note: Links highlighted in each panel correspond to a given cycle. Source: Consolidated Financial Statements for BHCs (Y-9C) and BHCs FR Y-14Q

\$$x$ short and pays \$$x$ less than its obligation to B. As we see here, the amount of cyclic loss, \$$x$, can not exceed any of the obligations along the cycle. Therefore, the minimum exposure along a cycle is an upper bound on the potential cyclic loss.

We utilize the minimum exposure along a cycle as a measure of riskiness of the cycle. For example, a cycle with a minimal smallest exposure (e.g., one cent) can only trigger a small loss for all banks involved. For this trigger cascading defaults, each bank must already be on the brink of default with a minuscule shortfall. Such a scenario warrants less attention of a theory of self-fulfilling failures compared to cycles with larger exposures. Therefore, weighting each cycle with the minimum exposure within a cycle provides a more accurate assessment of the potential risk the cycle poses.

Figure 19 implements this idea by weighting the cycle by the minimum exposure on the cycle in each quarter. For each quarter q and cycle χ we compute the minimum level of Gross CE exposure. We denote this value as $gce^{min}_{\chi,q}$. We then compute the average as $\overline{gce}^{min}_{\chi,q} = \sum_\chi gce^{min}_{\chi,q}/N^\chi_q$ where N^χ_q is the number of cycles observed in quarter q. In addition, we compute the sum of minimum exposures $Sgce^{min}_{\chi,q} = \sum_\chi gce^{min}_{\chi,q}$. Figure 19 presents the average $\overline{gce}^{min}_{\chi,q}$ and the sum $Sgce^{min}_{\chi,q}$ in the top panel and bottom panel, respectively. In both cases, we normalize these measures so the maximum value in the time series equals 1, which happens in 2013.Q2. This figure suggests that, in spite of the fluctuations in the number of cycles, when weighted by the minimum exposure (the relevance of each cycle), either in total or in average, there is not a considerable change over time.

Figure 19: Average and Sum of Minimum Exposures across cycles



Note: The top panel presents $\overline{gce}^{min}_{\chi,q}$ and the bottom panel $Sgce^{min}_{\chi,q}$. We normalize these measures so the maximum value in the time series equals 1. Source: Consolidated Financial Statements for BHCs (Y-9C) and BHCs FR Y-14Q

4.3 Centrality

Measures of centrality are used to quantify positions, prevalence, and importance of nodes in networks. In our context, we are interested in measures that reflect the importance of each bank with regard to their contribution to systemic risk. We propose two main measures. The first is related to the frequency with which a given bank is part of a cycle. We call this *involvement*. The second is related to resilience of each bank to shocks that can trigger cyclic failures. We call this *exposure to the cycles*.

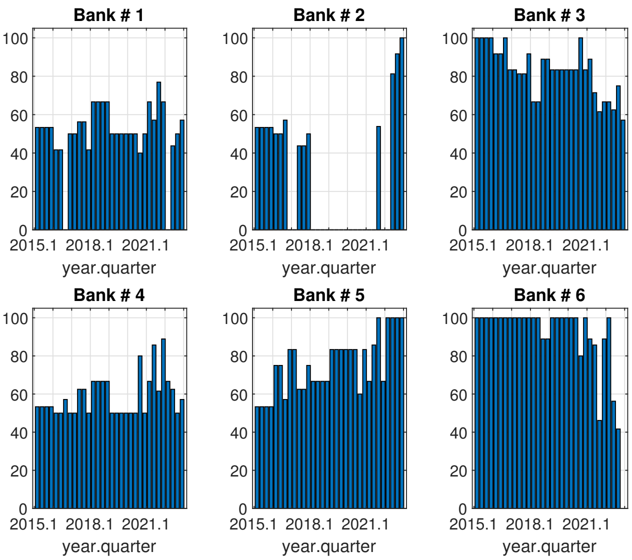
Involvement of banks in cycles. A bank's contribution to coordination failures depends on its frequency of participation in cycles. Figure 20 presents the fraction of total cycles per quarter in which each bank participates.

Notably, not all banks participate in every cycle, as evidenced by the average of 4 banks per cycle. However, there is heterogeneity in involvement. Some banks, particularly Bank 6 and, to a lesser extent, Bank 3, participate in nearly all cycles. In contrast, Banks 1 and 2 participate less frequently, with Bank 2 absent from any cycles during 2018 and 2019.

This observation is crucial for policy implications regarding cycle analysis. Bank 6, for instance, plays a central role in cycles, exposing it to potential coordination failures originating from shocks to other banks. When a bank is involved in numerous cycles, monitoring its portfolio to ensure resilience against cyclic shocks becomes crucial. Eliminating Bank 6's exposure would significantly reduce coordination failures across most cycles. Conversely, improving Bank 2's conditions and reducing its exposure would have a limited impact on mitigating other coordination failure channels.

Therefore, understanding bank involvement in cycles is essential for identifying key players and targeting interventions to effectively reduce systemic risk.

Figure 20: Fraction of cycles bank i participates in



Note: Total corresponds to the total number of cycles in a quarter. Number of cycles bank i corresponds to the number of cycles in which bank i is one of the nodes. Source: Consolidated Financial Statements for BHCs (Y-9C) and BHCs FR Y-14Q

Self-exposures of cycles. As previously discussed, all cycles can potentially generate coordination failures, but their magnitudes differ. The minimum exposure within a cycle determines the maximum cyclic self-fulfilling loss, thus serving as a proxy for the risk posed by the cycle. We can also examine each bank's contribution to this risk within a cycle.

To identify the bank most reliant on others fulfilling their obligations, we determine the bank holding the minimum exposure in each cycle and attribute this amount as a risk imposed by that bank. A bank frequently holding minimum exposures across cycles is more susceptible to self-fulfilling interbank losses and should be monitored closely as a potential early defaulter in a brewing coordination failure.

To evaluate the frequency of a bank holding the "key link" we compute the fraction of cycles per quarter where bank i induces the minimum exposure (i.e., the exposure of bank j to bank i is the minimum within the cycle). Let $\chi \in \chi_q = \{1, \ldots, N_q^{\chi}\}$ denote the set of cycles in quarter q, and $gce_{\chi,q}^{min}$ denote the minimum exposure in cycle χ. For each bank i, we compute:

$$N_{i,q}^{min} = \sum_{\chi \in \chi_q} \mathbb{I}_{\{gce_{\chi,q}^{i} = gce_{\chi,q}^{min}\}} \times \mathbb{I}_{\{i \in \chi, q\}}$$

, where $gce_{\chi,q}^{i}$ is the exposure induced by bank i in cycle χ during quarter q. Note that $N_{i,q}^{min} \in \{0, \ldots, N_q^{\chi}\}$.[38]

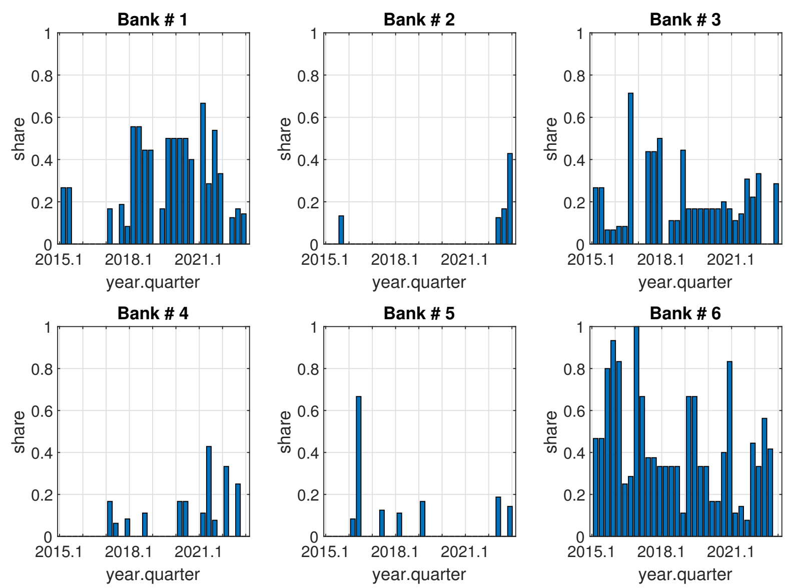
[38]It can be zero if the bank is not part of any cycle or if it does not induce the minimum exposure in any cycle

Figure 21 presents the ratio $N_{i,q}^{min}/N_q^{\chi}$ for each bank and quarter, indicating how frequently a bank holds the minimum exposure and thus how reliant its repayment ability is on receiving full interbank assets. Banks 2, 4, and 5 appear robust, participating in few cycles and rarely holding minimum exposures. Conversely, Banks 1, 3, and especially 6 exhibit non-negligible susceptibility to failures.

This measure complements the previous analysis on the number of cycles a bank participates in. For example, Bank 6 is central to numerous cycles, implying frequent exposure to coordination failures originating from shocks to other banks. This measure reveals that Bank 6 also often holds the minimum exposure, making it the weakest link in many cycles.

These findings have policy implications. Banks 1, 3, and 6 require close monitoring, not due to their inherent riskiness but because they are the most vulnerable to initial defaults in coordination failures. Strengthening these banks and their portfolios would be crucial in preventing the spread of coordination failures.

Figure 21: Share of Cycles in which bank i induces minimum exposure



Note: This figure shows $N_{i,q}^{min}/N_q^{\chi}$ for each bank. Source: Consolidated Financial Statements for BHCs (Y-9C) and BHCs FR Y-14Q

Self-Exposures of Cycles to Involved Banks. Finally, we consider instances where a bank holds the minimum exposure in a cycle, weighting this by the magnitude of the exposure. This provides a refined measure for identifying banks requiring close monitoring, combining their likelihood of signaling systemic problems with the size of the potential problem.

it belongs to. Conversely, it equals N_q^{χ} if the bank is part of every cycle in quarter q and induces the minimum exposure in all of them.

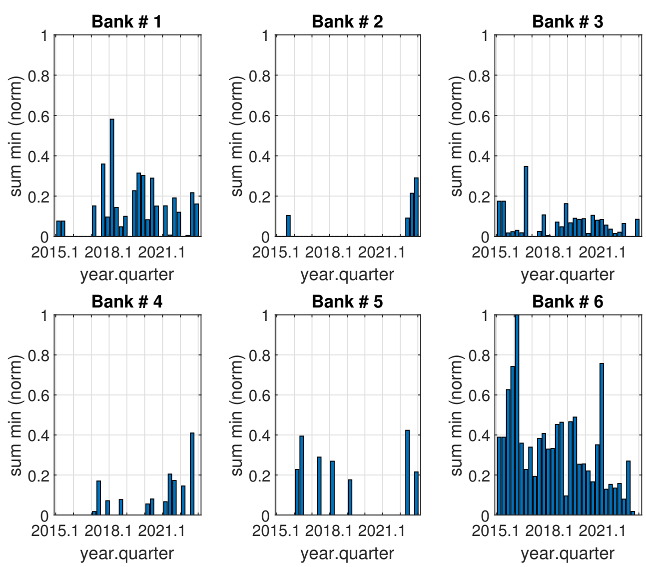
For each quarter, we calculate the sum of minimum exposures induced by bank i:

$$Sgce_q^{i,min} = \sum_{\chi \in \chi_q} gce^i_{\chi,q} \times \mathbb{I}_{\{gce^i_{\chi,q}=gce^{min}_{\chi,q}\}} \times \mathbb{I}_{\{i \in \chi,q\}}$$

Figure 22 presents this indicator normalized by the maximum value across banks and quarters. Bank 6 stands out, followed by Bank 1. This measure adds valuable information for policy considerations. Bank 6 is not only exposed to most cycles but also holds the highest exposure in terms of both frequency and magnitude, making it central to the spread of coordination failures.

Conversely, Bank 2 appears irrelevant to coordination cycles, being neither involved nor central. However, this raises a different policy concern. While Bank 2 is unlikely to propagate failures, it could be a trigger and source of failures. Its limited exposure to cycles implies that many other banks are exposed to it. Thus, a shock leading to Bank 2's default could trigger a cascade. Policymakers should not only monitor the resilience of Bank 6 against defaults but also the health of Bank 2 to prevent it from defaulting.

Figure 22: Normalized sum of minimum exposure by cycle and bank



Note: Figure shows $Sgce^{i,min}_{\chi,q} / \max_{i,q}\{Sgce^{i,min}_{\chi,q}\}$. Source: Consolidated Financial Statements for BHCs (Y-9C) and BHCs FR Y-14Q

5 Conclusions

In this paper, we examine the effects of recent regulations promoting central clearing of derivative contracts and offer a cautionary perspective. While these regulations assume that increasing clearing reduces systemic risk, we emphasize that the identity of the clearing parties and the details of clearing patterns are crucial. If multilateral netting is promoted at the expense of bilateral netting due to asymmetric or imbalanced clearing by counterparties, systemic risk may actually rise. Despite more clearing may reduce the likelihood crises originate at the core of the system, asymmetric clearing may increase the contagion towards periphery banks.

We present empirical evidence demonstrating asymmetric clearing of derivatives between periphery and core banks in the U.S. over the past decade. While core banks have maintained their relative rate of clearing, periphery banks have increased their clearing. This asymmetric response implies greater exposure to self-fulfilling cyclic failures, and systemic risk may indeed have increased within the banking system.

Theoretically, we propose a 'dome theory' of financial crises in which cycles are necessary for self-fulfilling coordination failures and their propagation through the network. We characterize the anatomy and evolution of cycles within the core, revealing the heterogeneous roles of banks. Some banks serve as potential conduits of contagion, while others are positioned at the source of shocks. Using confidential data, we provide evidence of the empirical relevance of these network properties within the U.S. banking system.

Our findings have several policy implications. First, regulators should monitor not only the extent of multilateral netting through clearing but also the evolution of bilateral netting among banks connected to cycles. Second, supervisors should pay attention to the diverse roles of banks within a cycle. Some banks act as potential conduits for contagion, necessitating robust portfolios to withstand counterparty defaults and break the cycle. Others are potential sources of contagion, requiring measures to minimize their default likelihood.

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Appendix

A-1 Regulatory Reforms

In this section, we provide a somewhat more detail description of the regulatory reforms.[39] The financial crisis in 2008 triggered a set of reforms aimed at increasing the resiliency of the financial sector. These reforms included changes in capital and liquidity requirements. Of particular importance for our analysis were changes regulations that focus on reducing counterparty credit risk via increasing central clearing.[40] These reforms included two key elements:

1. **Restrictions:** Standardized over-the-counter (OTC) derivatives are mandated to be cleared through central counterparties (CCPs).[41]

2. **Incentives:** Non-cleared derivatives are subject to higher capital (higher risk-weights) and collateral requirements.[42]

Most of the final rules were implemented between 2012 and 2015.[43] For most of the analysis, and consistent with our reading of the changes in the financial system, we focus on the period that starts in 2015.Q1 as the post-reform period.

Clearing Mandate: Among the new regulations, a key restriction arose from the mandate to clear a particular set of derivatives. The final rules requires certain classes of credit default swaps and interest rate swaps to be cleared. The relevant provisions for what derivatives were mandated to be cleared through a CCP are detailed within the Dodd-Frank Act, and enforced by the Commodity Futures Trading Commission (CFTC) and the Securities and Exchange Commission (SEC). In 2012, the CFTC issued final rules to implement the clearing requirement determination under section 723 of the Dodd-Frank Wall Street Reform and Consumer Protection Act. The final rules require certain classes of credit default swaps and interest rate swaps to be cleared by Derivative Clearing Organization (DCOs) registered with the Commission.[44]′[45] It is optional to centrally clear other derivatives such as

[39] See also Ghamami and Glasserman (2017) and the Financial Stability progress reports published since 2010 (https://www.fsb.org/).

[40] The initial proposal for reform was made in 2009, when G-20 Leaders agreed that all standardised OTC derivative contracts should be traded on exchanges or electronic trading platforms, where appropriate, and cleared through central counterparties (see FSB (2010)).

[41] A centrally cleared derivative contract is defined as "... a derivative contract is an exposure associated with an outstanding derivative contract that an institution, or an institution that is a clearing member has entered into with a central counterparty (CCP), that is, a transaction that a CCP has accepted." (see www.federalreserve.gov/reportforms/forms/FR_Y-9C20191231_i.pdf, link last accessed 05/24/2024). In our framework, these are the cleared exposures. Any other derivative contract is called OTC.

[42] Derivatives cleared through a CCP incur not only the capital charge due to the trade exposure but also a default fund capital charge (on average small).

[43] The original proposal also included collateral costs for OTC derivatives via margin requirements but those reforms were postponed several times and implemented only recently.

[44] In 2016, the CFTC issued a notice of proposed rulemaking that would require additional interest rate swaps to be cleared by DCOs registered with the Commission.

[45] See CFTC https://www.cftc.gov/LawRegulation/DoddFrankAct/Rulemakings/ClearingRequirement/index.htm for a list of the final rules (link last accessed 5/24/2024). The list of required derivatives can be found here https://www.cftc.gov/sites/default/files/idc/groups/public/@otherif/documents/ifdocs/clearingrequirementcharts.pdf

currency swaps, commodity swaps, equity swaps, and inflation swaps. [46]

Capital Regulation: Additionally, in order to increase the incentives to clear derivatives, risk-weights for OTC derivatives were set higher than for centrally cleared derivatives.More specifically if, as opposed to be traded over-the-counter, a derivative is centrally cleared the risk weight of the underlying exposure (e.g., 20 percent, 50 percent, or 100 percent) is replaced with the risk weight of the CCP (2% or 4% based on the conditions of the derivative). OTC derivatives are subject to capital requirements for counterparty credit risk as well as Credit Valuation adjustment (CVA) risk.[47] One important difference between cleared and non-cleared derivatives is that trades through a CCP incur not only a trade exposure capital charge but also a default fund capital charge. The default fund is a contribution that CCPs require of clearing members so that losses to the clearinghouse from the failure of one member could be mutualized among surviving members (see Ghamami and Glasserman (2017)). The contribution of the default fund to risk-weighted assets is on average small. According to the Tenth Financial Stability Progress Report on the implementation of OTC Derivatives Market Reforms (November 2014) by the time there was significant progress in the central clearing for interest rate products (while availability of central clearing in other asset classes is more limited) and the final capital standards for the treatment of banks' exposures to CCPs published in April 2014 were expected to start to take effect in 2015.

Collateral Costs: Both cleared and non-cleared derivatives involve collateral costs through margin requirements. However, CCPs require initial margins for clearing which can be separate from margins between original counterparties. Typically, derivatives that are centrally cleared require larger margin requirements than non-centrally cleared derivatives.[48]

A-2 Data Appendix

A-2.1 Data Sources and Variables

We work primarily with two data sets: (1) the Consolidated Financial Statements for Holding Companies (FR-Y9C) and (2) the Capital Assessments and Stress Testing Data (FR-Y14Q - Schedule L "Trading and Counterparty"). The FR-Y9C is public and collects financial data (balance sheet, income statement, and several other schedules including institution level values of off-balance sheet items)

[46] By far the largest proportion of activity is in interest rate derivatives. The next largest proportion of activity is in foreign exchange derivatives, followed by credit derivatives.

[47] The default capital charge is intended to cover losses due to default of the counterparty, while the CVA cpaitl charge addresses the potential mark-to-market loss caused by an increase in the credit spread of the counterparty.

[48] While the original Basel Committee proposal included a formal margin requirement for non-centrally cleared derivatives but the introduction of this requirement was only implemented after the pandemic. More specifically, in 2011, the G20 agreed to add margin requirements on non-centrally cleared derivatives. In 2015, the implementation of margin requirements was delayed until 2020 when due to the impact of the pandemic it was delayed an additional year. See BIS (2013) "Margin requirements for non-centrally cleared derivatives" (https://www.bis.org/publ/bcbs261.htm) and the versions of the document that followed. Regulatory guidelines require initial margin levels for non-cleared contracts to cover a 99% loss quantile of the netting set over a horizon of 10 days, as opposed to 3 to 5 days for cleared OTC contracts. For variation margin, the full amount necessary to fully collateralize the mark-to-market exposure of the non-centrally cleared derivatives must be exchanged.

at the bank holding company (BHC) level on a consolidated basis.[49] Only bank holding companies ("banks") with more than $3 billion in assets are required to report.[50] This report is published quarterly, as the last calendar day of the quarter.[51] Our second data source, the FR-Y14Q (schedule L), is confidential and used to support supervisory stress testing models and for continuous monitoring by the Federal Reserve.[52] We gained access to the "Trading and Counterparty" schedule that is submitted by the BHCs subject to supervisory stress tests each quarter.[53] Schedule L includes key information on counterparty risk is submitted by banks with significant derivative activity and allows us to construct a consistent time series for 6 reporting banks (most other banks start reporting after 2019 and not at a consistent frequency). These are the largest banks in the U.S. when sorted by assets: J.P. Morgan Chase, Bank of America, Wells Fargo, Citibank, Morgan Stanley, and Goldman Sachs. This is not much of restriction since derivative activity is highly concentrated. Four banks with the most derivative activity (J.P. Morgan Chase Bank, Bank of America, Citibank, and Goldman Sachs, which are included in our sample) hold 87.4 percent of all bank derivatives (by notional value). We call the six banks for which we construct the full picture of counterparty exposure in our sample "core" banks. We think of core banks as large and interconnected banks that pose systemic risks.

We combine primarily two non-confidential schedules from the FR-Y9C report: schedule HC-R ("Regulatory Capital") and schedule HC-L ("Derivatives and Off-Balance Items"). Using the schedule HC-R we can obtain estimates of derivative activity by risk-weights. Prior to 2015 it is not possible to distinguish between centrally cleared and non-cleared derivatives. However, since 2015, the report makes a distinction between Over-the-Counter derivatives and Centrally cleared derivatives across asset risk-weights.[54] This schedule also provides information on the type of derivative contract (e.g. interest rate, foreign exchange and gold, credit) and maturity buckets (e.g. 1 year or less, over one year through five years). Schedule HC-L also provides information on Notional amounts by derivative type as well as

[49] The information is used to assess and monitor the financial condition of holding company organizations, which may include parent, bank, and nonbank entities. See https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_Y-9C for a full description of the data and reporting forms and instructions.

[50] This asset threshold was implemented in 2018. The reporting threshold was $150 million before 2006, $500 million between 2006 and 2015, and $1 billion between 2015 and 2018.

[51] For example, the OCC Quarterly Report on Bank Trading and Derivative Activities is based on the FR-Y9C report. The latest report can be found here: https://www.occ.gov/publications-and-resources/index-publications-and-resources.html (link last accessed 5/24/2024).

[52] More information about FR Y-14Q reporting requirements, instructions and forms can be found at: https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_Y-14Q.

[53] Banks that comply with the following requirements submit these regulatory forms: (1) have aggregate trading assets and liabilities of $50 billion or more, or aggregate trading assets and liabilities equal to 10 percent or more of total consolidated assets, and (2) are not "large and noncomplex firms" under the Board's capital plan rule. A large and noncomplex firm is a BHC with total consolidated assets of at least $50 billion but less than $250 billion, total consolidated nonbank assets of less than $75 billion, and is not a U.S. Globally systemically important bank (GSIB).

[54] When using this split the report uses credit equivalent which adds current credit exposure (sometimes refereed to as the replacement cost) plus the potential future exposure over the remaining life of the derivative contract. The current credit exposure is (1) the fair value of the contract when the fair value is positive and (2) zero when the fair value is negative or zero. Bilateral netting agreement between the reporting bank and a counterparty may ne taken into consideration.

the gross positive fair value (GPFV) and the gross negative fair value (GNFV). The GPFV corresponds to the total of all contracts with positive value (i.e., derivative receivables) to the bank and represents a key measure of credit exposure (i.e., these are the contracts on which a bank would lose value if the counterparty of a contract defaulted). The GNFV represents a measure of the exposure the bank poses to its counterparties.

The L schedule from the FR-Y14Q contains 18 sub-schedules and provides unique information about the derivative profile by counterparty as well as aggregated across all counterparties of each reporting bank. We use sub-schedules L1.a, L1.b, L1.c, L1.d, and L1.e for most of the analysis. Sub-schedule L1.e provides information at the aggregate level distinguishing between exposures where the counterparty is a CCP and not. Sub-schedule L1.a report Top counterparties comprising 95% of firm Credit Valuation Adjustment (CVA) ranked by CVA, L1.b reports the Top 20 counterparties (for earlier periods) or the Top counterparties comprising 95% of firm stressed CVA for the most recent periods, L1.c and L1.d (available only until 2020.Q1) report the top 20 counterparties ranked by Net (of collateral) Credit Exposure and the Top 20 collateralized counterparties ranked by Gross Credit Exposure, respectively.[55] Counterparties are not repeated across sub-schedules so aggregating across all of them provides a more comprehensive picture.[56]

Possible BHCs counterparties include (but are not limited to) other BHCs, financial institutions (domestic and foreign), sovereigns and central counterparties. Designated central clearing counterparty (CCP) exposures include both cleared over-the-counter (OTC) derivatives and exchange traded derivatives. All counterparties have a unique identifier and firms provide the name and type of the counterparty which allows as to track relationships over time, with information on the industry code (six digit NAICS code), the country of domicile of the counterparty, an internal rating, and (when available) the external rating of the counterparty.[57] We focus on the network within U.S. counterparties. We document the changes in exposures using mostly Gross Credit Exposure (Gross CE) and Net Credit Exposure (Net CE). Gross CE is pre-collateral exposure after bilateral counterparty netting. Sometimes referred to as the replacement cost or current credit exposure, Gross CE is the fair value of a derivative contract when that fair value is positive. Gross CE is zero when the fair value is negative or zero. Net CE is Gross CE less the value of collateral posted by the counterparty to secure those trades.[58]

Table A.1 presents the key variables we use from each source.

[55] CVA is the value of credit risk for a particular counterparty.

[56] We discuss the coverage below as some large exposures can have small CVA exposure and not be included in sub-schedules L1a and L1b which provide the bulk of the exposure data. Subschedule L1.e allows us to obtain a comprehensive picture of CCP exposure.

[57] The reporting requirements by type of counterparty changes over time as the data requirements evolved during the last decade.

[58] Only collateral that was actually exchanged is incorporated in the Net CE reporting.

Table A.1: Key Variables by Source

Variable		Period	Source
Assets	bhck2170	1981.q2 - today	FR-Y9C
Liabilities	bhck2948	1981.q2 - today	FR-Y9C
Equity	bhck3210	1981.q2 - today	FR-Y9C
Gross Positive Fair Value	bhckc219 + bhckc221	2002.q1 - today	FR-Y9C
Gross Negative Fair Value	bhckc220 + bhckc222	2002.q1 - today	FR-Y9C
OTC Derivatives	bhcks542 + bhckh309	2015.q1 - today	FR-Y9C
by risk-weight	bhcks543 bhckhk00	2015.q1 - today	FR-Y9C
	bhckhk01 bhcks544	2015.q1 - today	FR-Y9C
	bhcks545	2015.q1 - today	FR-Y9C
	bhcks546 bhcks547	2015.q1 - today	FR-Y9C
	bhcks548 bhckh309	2015.q1 - today	FR-Y9C
Centrally Cleared Derivatives	bhcks549	2015.q1 - today	FR-Y9C
by risk-weight	bhcks550 bhcks551	2015.q1 - today	FR-Y9C
	bhcks552 bhcks554	2015.q1 - today	FR-Y9C
	bhcks555 bhcks556	2015.q1 - today	FR-Y9C
	bhcks557	2015.q1 - today	FR-Y9C
Subschedule ID	cacvm926	2015.q3 - today	FR-Y14Q
Counterparty Name	cacvm900	2013.q3 - today	FR-Y14Q
Industry Code	cacvr620	2013.q3 - today	FR-Y14Q
Country	cacvm905	2013.q3 - today	FR-Y14Q
Gross Current Exposure (GCE)	cacvm908	2013.q3 - today	FR-Y14Q
Net Current Exposure (NCE)	cacvm912	2013.q3 - today	FR-Y14Q
Credit Valuation Adjustment (CVA)	cacvm916	2013.q3 - today	FR-Y14Q
Default Fund (CCPs)	cacsr554	2015.q3 - today	FR-Y14Q

Figure A.1 presents a comparison between the aggregate levels reported in sub-schedule L1e and the aggregate values from sub-schedules L1a-d. The coverage is significant both for Gross CE and Net CE. It is important to note that sub-schedule L1e provides the aggregate exposure to CCP so this figure shows a lower bound on the coverage of our data when discussing patterns at the counterparty type level.

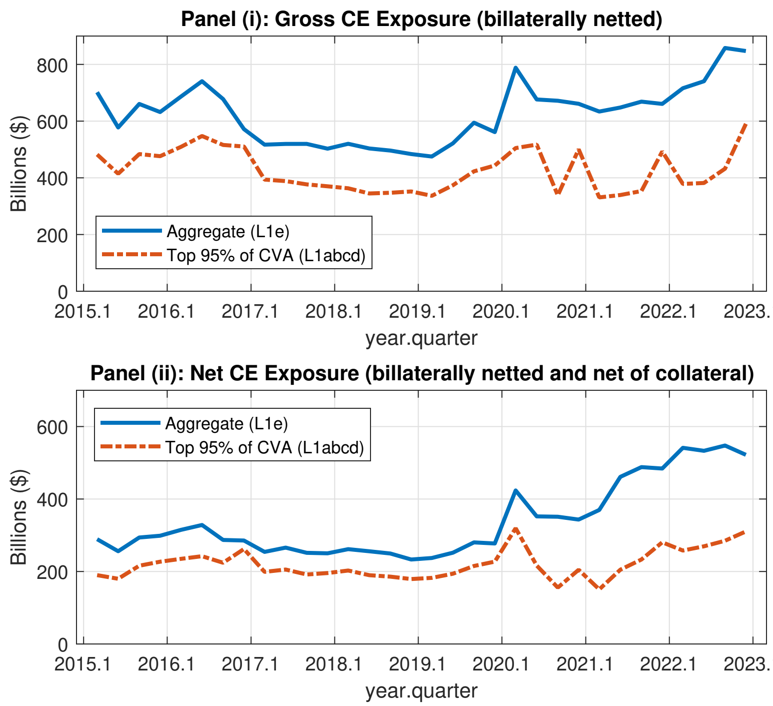
Figure A.2 shows that the decline in exposure to core banks post 2021.Q1 is associated with an increase in exposure to non-financial corporations as well as an increase in exposure to nonbank financial institutions. In 2022.Q4 non-financial corporations and nonbank financial institutions account for 40.6% and 9% of total GCE exposures (among U.S. counterparties).

Figure A.3 presents exposure by counterparty types using GCE for all counterparties (U.S. and foreign).

Figure A.4 presents the average exposure for core banks when use Net CE as the measure of exposure.

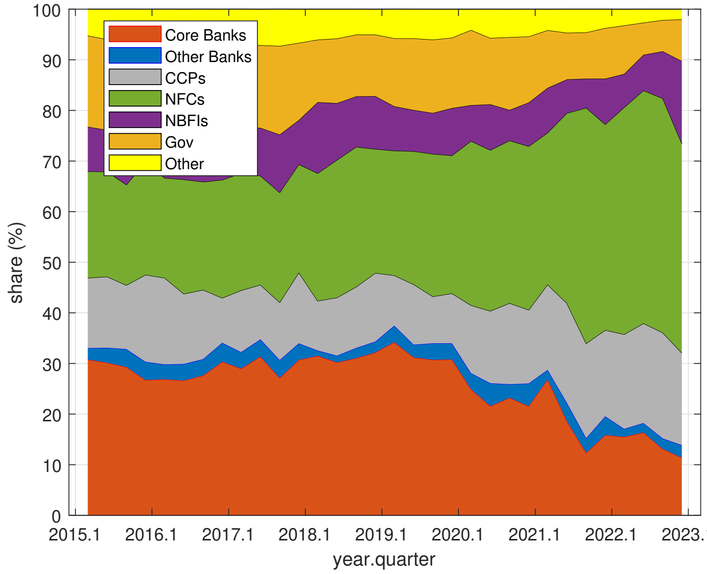
Nodes per cycle: Figure A.7 shows the number of cycles, the minimum number of nodes, the maximum number of nodes, and the average number of nodes involved in a cycle for every period in our sample. This is an important part of the anatomy of cycles when extending the model to efforts to coordinate and avoid the coordination failure. In principle, the more banks are involved in a cycle the harder it is to coordinate and avoid self-fulfilling defaults. As it is clear from the figure, we need at least three banks on a cycle, but in average there are 4 banks involved. This is also the case in which the anatomy of cycles has not changed much in our studied timeframe.

Figure A.1: Comparison L1 sub-schedules a,b,c,d,e (core banks)



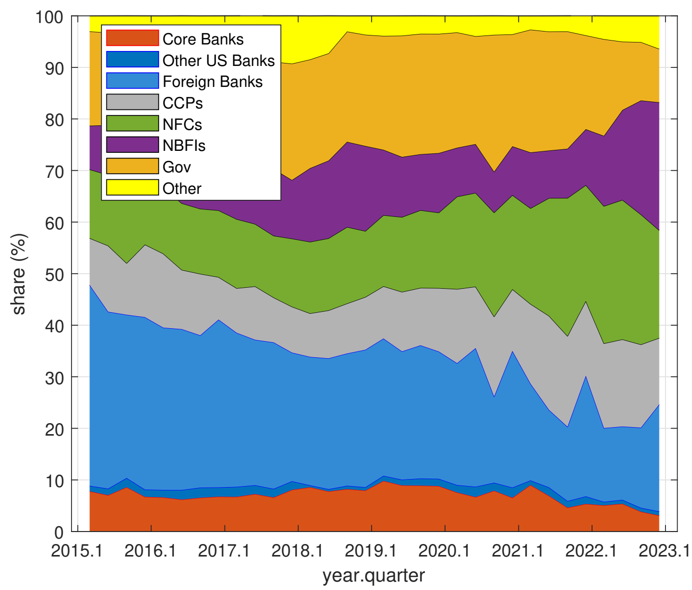
Note: GCE corresponds to Gross credit exposure and NCE to Net Credit Exposure. Aggregate (L1e) refers to the totals according to sub-schedule L1e which reports aggregate data by rating and collateralization. Top 95% of CVA (L1abcd) correspond to aggregates using sub-schedules L1a, L1b, L1c, L1d which report exposures by counterparty for counterparties comprising 95% of firm Credit Valuation Adjustment (CVA). (L1a unstressed CVA, L1b stressed CVA, Source: Consolidated Financial Statements for BHCs (FR-Y9C) and BHCs FR-Y14Q (schedule L)

Figure A.2: Counterparty Exposure Gross CE (all U.S. counterparties by type)



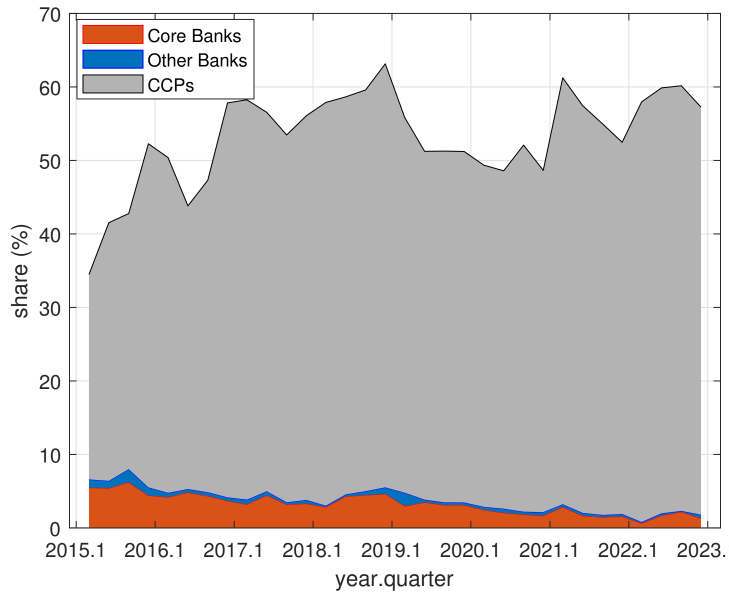
Note: Asset weighted average of bank level GCE. GCE refers to Gross credit exposure (bilaterally netted). Figure present exposures for US counterparties. “CCPs” corresponds to Central Counterparty, “Other Banks” to other banks not in the “Core Banks” category, “NFCs” corresponds to Non-Financial Corporations, “NBFIs” corresponds to nonbank financial intermediaries and includes insurance companies, pension funds, special purpose vehicles, and other nonbank financial companies, “Gov” refers to government entities, “Other” includes all counterparties not previously classified. Source: Consolidated Financial Statements for BHCs (FR-Y9C) and BHCs FR-Y14Q (schedule L)

Figure A.3: Counterparty Exposure Gross CE (all counterparties by type)



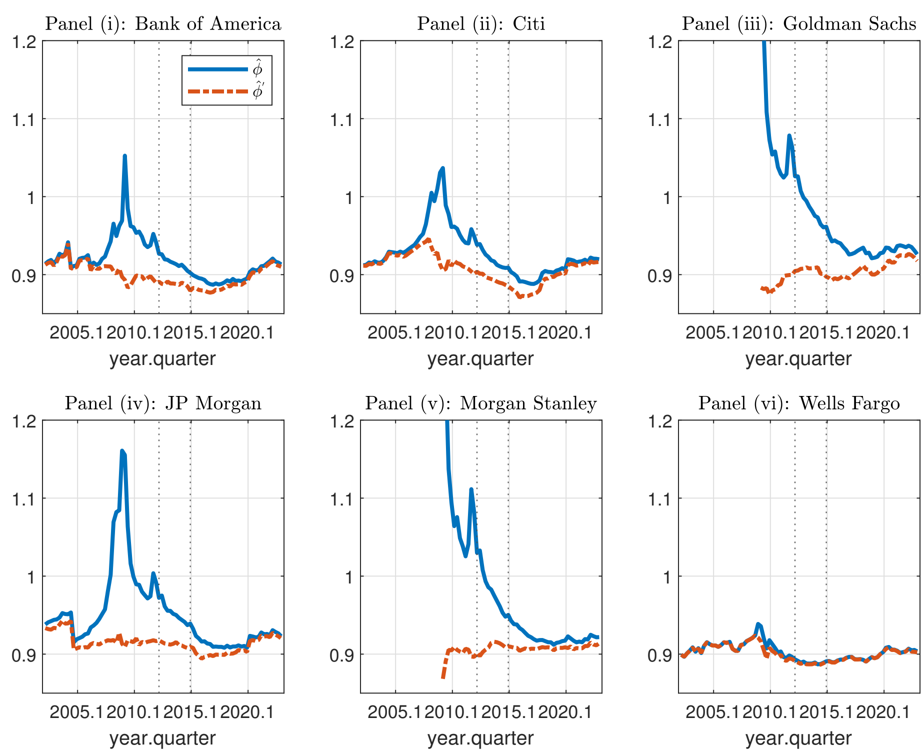
Note: Asset weighted average of bank level GCE. GCE refers to Gross credit exposure (bilaterally netted). Figure present exposures for all counterparties (i.e., US and Foreign). “CCPs” corresponds to Central Counterparty, “Other US Banks” to other US banks not in the “Core Banks” category, “Foreign Banks” refers to foreign banks, “NFCs” corresponds to Non-Financial Corporations, “NBFIs” corresponds to nonbank financial intermediaries and includes insurance companies, pension funds, special purpose vehicles, and other nonbank financial companies, “Gov” refers to government entities, “Other” includes all counterparties not previously classified. Source: Consolidated Financial Statements for BHCs (FR-Y9C) and BHCs FR-Y14Q (schedule L)

Figure A.4: Counterparty Exposure Net CE (U.S. counterparties by type)



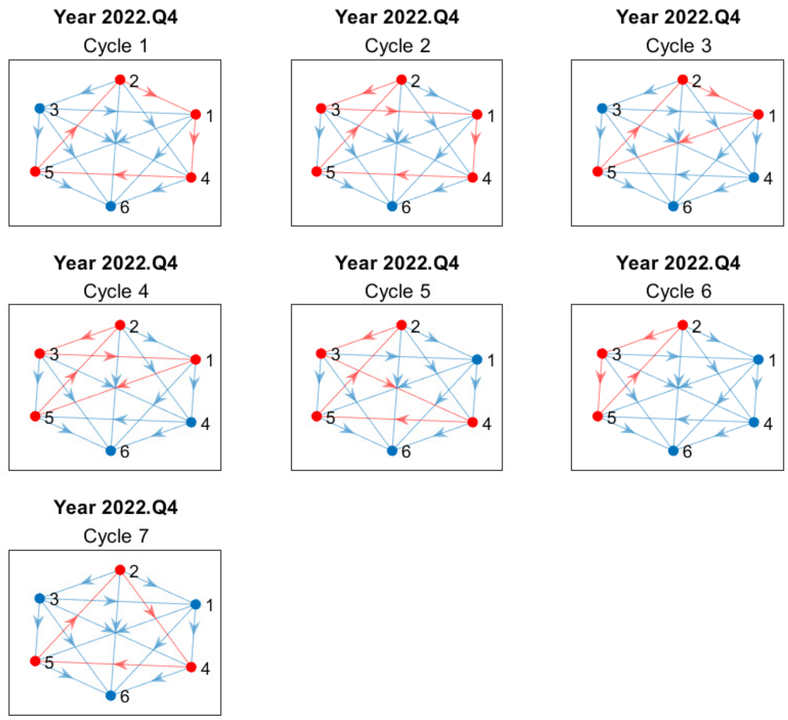
Note: Asset weighted average of bank level Net credit exposure by counterparty type. Net Credit Exposure corresponds to Gross credit exposure (bilaterally netted) net of collateral. Figure present exposures for US counterparties. "CCPs" corresponds to Central Counterparty, , "Core" corresponds to the reporting banks, "Other Banks" to other banks not in the "Core" category. Source: Consolidated Financial Statements for BHCs (FR-Y9C) and BHCs FR-Y14Q (schedule L)

Figure A.5: Coordination Failure Region (ϕ and $\hat{\phi}'$) by bank



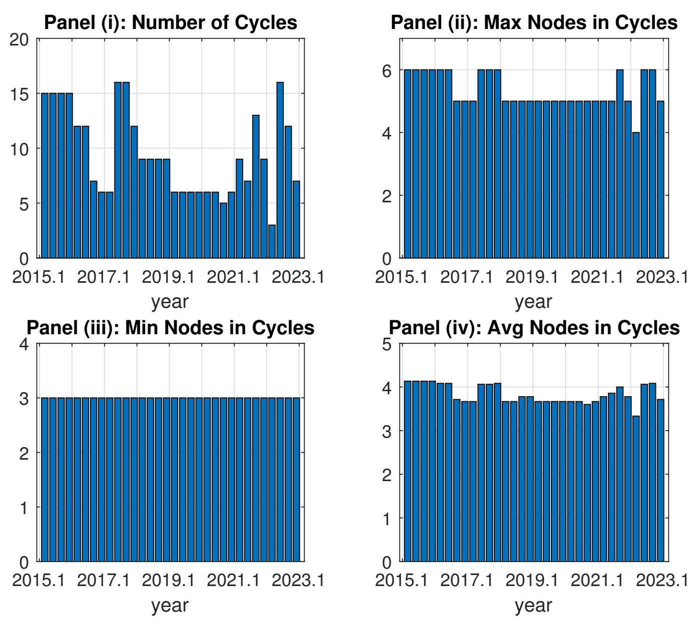
Note: Figure shows $\hat{\phi}$ (see equation 5) and $\hat{\phi}'$ (see equation 6) by bank.
Dotted vertical lines correspond to a period of transition after reforms were announced but not yet fully implemented. We define the post-reform period that starts in 2015.Q1 Source: Consolidated Financial Statements for BHCs (FR-Y9C)

Figure A.6: Cycles Banking Network 2022.Q4



Note: Each panel shows exposures across core banks (numbered 1-6) of GCE (Gross Credit Exposure). Links highlighted in each panel correspond to a given cycle. Direction of arrows $j \rightarrow i$ indicates bank i is exposed to j. Source: BHCs FR Y14Q Schedule L

Figure A.7: Cycles Statistics



Note: Links highlighted in each panel correspond to a given cycle. Source: BHCs FR-Y14Q

A-3 Theory Appendix

Proofs of Proposition 1, Proposition 2, Theorem 3 follow immediately from the discussions in the main body.

Proof of Theorem 4

In the benchmark of no clearing, we have

$$\begin{aligned} i \in K : D_i &= \sum_{j \in K} \langle D_{ij}^{**} - D_{ji}^{**} \rangle + \sum_{j \in P} \langle D_{ij}^{**} - D_{ji}^{**} \rangle \\ i \in P : D_i &= \sum_{j \in K} \langle D_{ij}^{**} - D_{ji}^{**} \rangle \end{aligned}$$

For $i \in P$, let $X_{ij} \in [0, D_{ji}^{**}]$ be the amount cleared by i from its exposures $E_{ij}^{**} = D_{ji}^{**}$ to j. Then

$$\begin{aligned} i \in K : D_i' &= \sum_{j \in K} \langle D_{ij}^{**} - D_{ji}^{**} \rangle + \sum_{j \in P} \langle (D_{ij}^{**} - X_{ji}) - D_{ji}^{**} \rangle + \langle \sum_{j \in P} X_{ji} \rangle \geq D_i \\ i \in P : D_i' &= \sum_{j \in K} \langle D_{ij}^{**} - (D_{ji}^{**} - X_{ij}) \rangle + \langle \sum_{j \in P} -X_{ij} \rangle \geq D_i \end{aligned}$$

For $i \in K$, equality $D_i' = D_i$ holds iff $X_{ji} \leq D_{ij}^{**} - D_{ji}^{**}$ for all $j \in P$. For $i \in P$, equality $D_i' = D_i$ holds iff $X_{ij} = 0$ for all $j \in K$. So in general, coordination failure region expands strictly unless there is no clearing by the periphery either.

Proof of Proposition 5

If $\delta_{KK} < 0$, all cycles are cleared out. So $\Phi = 0$.

If $\delta_{KK} > 0$, $\delta_{KP} > 0$, $\delta_{PK} > 0$ is the benchmark case of no clearing.

$$\begin{aligned} D_{i \in K}^{*} &= \sum_{j \in K} \langle D_{ij}^{**} - D_{ji}^{**} \rangle + \sum_{j \in P} \langle D_{ij}^{**} - D_{ji}^{**} \rangle \\ D_{i \in P}^{*} &= \sum_{j \in K} \langle D_{ij}^{**} - D_{ji}^{**} \rangle \end{aligned}$$

If $\delta_{KK} > 0$, $\delta_{KP} < 0$, $\delta_{PK} < 0$,

$$\begin{aligned} D_{i \in K} &= \sum_{j \in K} \langle D_{ij}^{**} - D_{ji}^{**} \rangle + \langle \sum_{j \in P} D_{ij}^{**} - D_{ji}^{**} \rangle \leq D_{i \in K}^{*} \\ D_{i \in P} &= \langle \sum_{j \in K} D_{ij}^{**} - D_{ji}^{**} \rangle \leq D_{i \in P}^{*} \end{aligned}$$

So bank by bank, ϕ_i decreases.

If $\delta_{KK} > 0$, $\delta_{KP} > 0$, $\delta_{PK} < 0$,

$$D_{i\in K} = \sum_{j\in K} \langle D_{ij}^{**} - D_{ji}^{**} \rangle + \sum_{j\in P} \langle -D_{ji}^{**} \rangle + \langle \sum_{j\in P} D_{ij}^{**} \rangle \geq D_{i\in K}^{*}$$
$$D_{i\in P} = \sum_{j\in K} \langle D_{ij}^{**} \rangle + \langle \sum_{j\in K} -D_{ji}^{**} \rangle \geq D_{i\in P}^{*}$$

So bank by bank, ϕ_i increases.

If $\delta_{KK} > 0$, $\delta_{KP} < 0$, $\delta_{PK} > 0$,

$$D_{i\in K} = \sum_{j\in K} \langle D_{ij}^{**} - D_{ji}^{**} \rangle + \sum_{j\in P} \langle D_{ij}^{**} \rangle + \langle \sum_{j\in P} -D_{ji}^{**} \rangle \geq D_{i\in K}^{*}$$
$$D_{i\in P} = \sum_{j\in K} \langle -D_{ji}^{**} \rangle + \langle \sum_{j\in K} D_{ij}^{**} \rangle \geq D_{i\in P}^{*}$$

So bank by bank, ϕ_i increases.