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Systemic Risk in Financial Networks: A Survey

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Abstract

We provide an overview of the relationship between financial networks and systemic risk. We present a taxonomy of different types of systemic risk, differentiating between direct externalities between financial organizations (e.g., defaults, correlated portfolios, fire sales), and perceptions and feedback effects (e.g., bank runs, credit freezes). We also discuss optimal regulation and bailouts, measurements of systemic risk and financial centrality, choices by banks regarding their portfolios and partnerships, and the changing nature of financial networks.

> The difficult task before market participants, policymakers, and regulators with systemic risk responsibilities such as the Federal Reserve is to find ways to preserve the benefits of interconnectedness in financial markets while managing the potentially harmful side effects.
>
> —Janet Yellen (2013)

1. INTRODUCTION

International finance has grown dramatically in past decades, paralleling the growth in international trade. For instance, the amount of investment around the world coming from foreign sources went from 26 trillion dollars in 2000 to over 132 trillion dollars in 2016, which represents more than a third of the total level of world investments (see Lund & Härle 2017). In addition, the financial sector is characterized by strong interdependencies, and therefore capital is circulating not only between countries but also from one financial institution to another. Using administrative data from the US Federal Reserve Bank, Duarte & Jones (2017) estimate that 23% of the assets of bank holding companies come from within the US financial system, as well as 48% of their liabilities—almost half.

Globalization, and its associated economies of scope and scale, has paid enormous dividends in terms of increased peace and prosperity. However, the associated increasingly interconnected financial network among ever-larger nodes also paves the way for systemic risk. Interdependencies between financial institutions can act as amplification mechanisms and create channels for a shock in one part of the system to spread widely, leading to losses that are much larger than the initial changes in fundamentals. These are not idle concerns, as we witnessed in 2008 when exposure to a problematic mortgage market led to key insolvencies in the United States and elsewhere, as well as to a broad financial crisis and prolonged recession.[1]

Financial markets are ripe with externalities as the fates of institutions depend upon each other in a variety of ways. At a most basic level, insolvencies involve substantial costs that are then passed on via defaults and drops in equity values, especially if left to cascade. The externalities are clear: If one organization has poor judgment in its investments, poorly managed business practices, or even just unusually bad luck, this ends up affecting the values of its partners, and then of its partners' partners; and this happens in discontinuous ways. There are also many other forms of externalities in financial networks, including bank runs, changes in asset values due to fire sales, inferences that investors make about one institution based on the health of another, and credit freezes.[2] Although some of these risks can be hedged, there are no markets for insurance against many of them. The externalities mean that the system as a whole can experience crises that are much broader and costlier than the independent failures that ignite them—hence the notion of systemic risk.

Many forms of systemic risk can be mitigated or even avoided altogether via appropriate oversight and judicious intervention. However, this requires a detailed view of financial interdependencies and an understanding of their consequences as well as of the incentives that different parties in the network have. These are the focus of what follows.

The growth in the study of networks over the past decades has provided us with tools to better understand systemic risk.[3] It is an ideal time to provide a conceptual framework within which we

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[1] For narratives of the crisis, readers are referred to Financ. Crisis Inq. Comm. (2011), as well as Glasserman & Young (2016) and Jackson (2019).

[2] We do not directly address the issue of bubbles in this review, but one can find extensive treatments elsewhere (e.g., Shiller 2015).

[3] For detailed overviews of the broader networks literature, readers are referred to Jackson (2008, 2019). References on financial networks appear in an early review by Summer (2013), and references to more recent

can organize the main insights we gained. In what follows, we draw a distinction between two types of systemic risk: (*a*) contagion through various channels that generate externalities among financial institutions (e.g., defaults, correlated portfolios, and firesales), and (*b*) self-fulfilling prophecies and feedback effects (e.g., bank runs, credit freezes, equilibrium multiplicities). We then discuss how each sort of risk depends on the network of interdependencies. Finally, we use this taxonomy to examine how systemic risk is affected by banks' incentives to choose their investments and partners, how to measure systemic risk and financial centrality, and when and how to intervene or regulate.

Some background on empirical analyses and facts about financial networks appear in the **Supplemental Appendix**, along with an executive summary of this survey.

Supplemental Material >

2. A TAXONOMY OF SYSTEMIC RISK IN FINANCIAL NETWORKS

Defaults and financial crises are as old as investment: from the immense credit crunch under Emperor Tiberius in 33 CE to the repeated external defaults by most countries involved in the Napoleonic wars to the recurring bank runs and panics of the nineteenth century. The variety of ways that such crises erupt and play out (e.g., Reinhart & Rogoff 2009) calls for a taxonomy of the externalities that lead to systemic problems.

We provide a two-layer taxonomy. We first distinguish between (*a*) contagion through direct externalities (e.g., when a default by one bank leads to distress for another, or a fire sale of one bank's assets depresses the value of another bank) and (*b*) various feedback effects that allow for multiple equilibria and self-fulfilling prophecies (e.g., when beliefs about the poor condition of a bank become self-fulfilling as they lead investors to call in their loans). Within these two types of systemic risk, there is a second layer of different ways in which each can work. Before presenting this taxonomy, we discuss what constitutes a financial network under different scenarios.

2.1. What Constitutes a Financial Network?

Financial networks are complex systems in which many institutions are interconnected in various ways. First and foremost, institutions are linked through financial contracts: They lend to and borrow from each other to smooth idiosyncratic liquidity variations and meet deposit requirements; they collaborate on investment opportunities; and they operate in chains, repackaging and reselling assets to each other. These networks of interdependencies are the focus of a large part of the literature (e.g., Allen & Gale 2000, Eisenberg & Noe 2001, Elliott et al. 2014).

Second, even when financial institutions are not transacting directly, commonality in their exposures leads to a correlation in their values. This can be tracked via a network in which a (weighted) link between two institutions captures the correlation between their portfolios (Acharya & Yorulmazer 2007, Allen et al. 2012, Diebold & Yılmaz 2014, Cabrales et al. 2017).

There is also a burgeoning literature tying these different forms of interdependency together. In Heipertz et al. (2019), banks trade outside and interbank assets, and prices adjust to clear the markets. The network is the reduced-form relationships between banks' equity values in equilibrium: The weighted edge from i to j captures the partial equilibrium effect of a drop in the value of i on the value of j, given induced shifts in trades and prices.

papers appear throughout this review. Jackson (2019, chapter 4) details a financial crisis and discusses some key aspects of financial markets and policy prescriptions.

Although the nature of the financial network varies across models, all models highlight the same fact: Financial interdependencies generate systemic risks. A formal model of financial networks is thus useful to measure, predict, and trace the sources of systemic risk. Hence, we introduce a framework that encompasses many in the literature and that allows us to distinguish between two types of systemic risk.

Let $N = \{1, \ldots, n\}$ be a set of financial institutions. We call them banks, but they should be understood more broadly as any institution in the financial system whose actions affect others.

The network is characterized by a matrix $\mathbf{G} = (g_{ij})_{ij}$ such that g_{ij} captures the connection between bank i and j. A connection g_{ij} can have multiple components, each corresponding, for instance, to a different type of financial contract.[4]

A key object of interest is the vector of values associated with each institution, $\mathbf{V} = (V_i)_i$, accounting for all assets and liabilities, including any defaults and associated bankruptcy costs. Because banks are interconnected, their values depend on each other. The value of bank i is a function of other banks' values, denoted by $V_i = F_i(\mathbf{V} \mid \mathbf{G})$. Banks' values are then the solution to a system of n equations in n unknowns, written as

$$\mathbf{V} = F(\mathbf{V} \mid \mathbf{G}). \qquad 1.$$

Under some conditions, in particular that $F(\cdot \mid \mathbf{G})$ is nondecreasing and bounded in $\mathbf{V}$,[5] Tarski's fixed point theorem applies, and there exists an equilibrium—that is, values, consistent with each other, that solve Equation 1. Therefore, the term "equilibrium" simply refers to coherent accounting rather than to a fixed point of best responses or of some dynamic system. There can exist multiple equilibria, and the set of equilibria forms a complete lattice: There are maximum and minimum equilibria that take on the highest and lowest possible equilibrium values for all institutions simultaneously, which we call the best and worst equilibria in what follows.[6]

We distinguish between two sources of systemic risk that are generated by interdependencies between banks. First, a change in the value of bank i affects bank j, whose value changes by $\partial F_j / \partial V_i$. This then affects the values of the banks connected to j, and so on: A change in one bank's value spreads through the network and has far-reaching consequences. This form of risk is the focus of much of the literature on financial contagion. The second type of systemic risk stems from the multiplicity of equilibria and the possible shift from one equilibrium to another. Even in the absence of any change in the values of fundamental investments, network interdependencies can lead to self-fulfilling feedback effects whereby changes in beliefs become realized. So the first type of systemic risk captures how a change in fundamentals can move through the network—formally, how much equilibrium values $\mathbf{V}$ change in response to some initial change in fundamentals, while keeping the equilibrium constant—whereas the second type of systemic risk captures shifts between equilibria.[7] A contagion-based crisis is triggered by a change in

[4]Thus, it may be a multigraph; or one can think of it as multiplexed, that is, including layered networks. The different types of contracts can interact, as shown by Bardoscia et al. (2017) for UK bank data.
[5]That is, if $V_i' \geq V_i$ for all i, then $F(V' | \mathbf{G}) \geq F(\mathbf{V} | \mathbf{G})$, and the set of feasible $\mathbf{V}$'s is bounded above and below.
[6]The best and worst equilibria can be found via a simple algorithm: Start with the maximum possible values $V^{\max}$ (or minimum to find the worst) and then iteratively apply the function F. In many financial models, the convergence is fast (see, e.g., Eisenberg & Noe 2001, Jackson & Pernoud 2020), as the base asset values drive the equations, whereas with more arbitrary interdependencies finding the equilibria can be much slower (e.g., see Etessami et al. 2019).
[7]The distinction between these two types of systemic risk is reminiscent of the two views of financial crises brought forward in the literature: the business cycle view and the panic view (Allen & Gale 2007). In the former, crises are driven by changes in fundamentals, whereas in the latter crises are self-fulfilling prophecies that can be triggered solely via beliefs and behaviors.

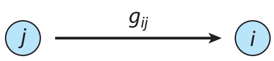

Figure 1

Bank j owes a debt of size g_{ij} to i.

fundamentals, whereas what triggers an equilibrium shift can be more nebulous. In the context of financial networks, an equilibrium shift can often be interpreted as a market freeze, which is likely to be driven by an increase in uncertainty that leads banks and others to be less trusting of their counterparties.

In the rest of this section, we discuss these two different forms of systemic risk and identify corresponding externalities and market imperfections that generate inefficiencies.

2.2. Contagion Through Network Interdependencies

We discuss direct transmission of distress via counterparty risk and commonality in exposures.

2.2.1. Cascades of insolvencies. A canonical form of contagion is a cascade of insolvencies. A bank gets low returns on its investments and cannot pay its debts. As those liabilities are defaulted upon, the balance sheets of other institutions worsen, leading some of them to become insolvent. As more become insolvent, the values of others are further depressed, and this cascades through the network.

Consider the two-bank relationship depicted in **Figure 1**, and let it represent a debt claim: g_{ij} indicates that j owes a debt D_{ij} to i, and arrows point in the direction in which value should flow. In this example , we have that $g_{ij} = D_{ij}$. Interbank contracts generate interdependencies between banks' (book) values, that is,

$$V_i = F_i(\mathbf{V} \mid \mathbf{G}) = \pi_i + \sum_j (d_{ij}(\mathbf{V}) - D_{ij}),$$

where π_i is the value of bank i's portfolio of outside investments,[8] and $d_{ij}(\mathbf{V})$ is the amount j can manage to pay to i. Because of limited liability, the value of this debt equals

$$d_{ij}(\mathbf{V}) = \min\left\{D_{ij}, \frac{D_{ij}}{\sum_k D_{kj}}\left[\pi_j + \sum_k d_{jk}(\mathbf{V})\right]\right\}.$$

For simplicity we have equalized the priority of all debt. Here, $\pi_j + \sum_k d_{jk}(\mathbf{V})$ is the value that j has available to pay its debts, which is then divided across creditors in proportion to their claims on j. More generally, the function would be a nested function reflecting priorities.

To see how interdependencies generate systemic risk, let $D_{ij} = 1$ and $\pi_i = 0.5$, and suppose that j's outside portfolio value drops from $\pi_j = 1.5$ to $\pi'_j = 0.5$. Bank values start at $V_i = 1.5$ and $V_j = 0.5$ under π, but under π' they fall down to $V_i = 1$ and $V_j = -0.5$ (or effectively to 0, given limited liability). Though the shock affects the portfolio of bank j, it also depresses the value of the other bank. The decrease in bank i's value could then lead to its default if i had debts to others.

This sort of cascade does not lead to additional losses beyond the drop in portfolio value. However, so far we have ignored the fact that insolvencies involve substantial bankruptcy costs. For instance, an extra 0.5 in bankruptcy costs would lead to $V_i = 0.5$ and $V_j = -1$ under π'. Each

[8]These are investments that are not in other financial institutions, such as mortgages, loans to nonfinancial companies, equities, etc.

additional insolvency then leads to deadweight losses to the system, and the overall cost can greatly exceed the initial shock. Also lost are some of the investment and lending services of the insolvent banks.

Early models of counterparty risk include those of Rochet & Tirole (1996) and Allen & Gale (2000), and they model the behaviors of banks and depositors. For example, Allen & Gale (2000) consider banks that are subject to liquidity shocks (e.g., unanticipated withdrawals). To insure against the shocks, banks can exchange part of their deposits ex ante. In the absence of aggregate uncertainty, the first-best allocation can be implemented through cross-bank claims, with a complete network of cross-deposits. The banks that need early liquidity get it from banks that have excess liquidity. However, these claims generate financial instability and contagion upon the realization of a shock that either was unanticipated or hit several banks, or when the network is not appropriately connected. Then, liquidity drawn by one bank from another can lead illiquidity to cascade.

Eisenberg & Noe (2001) propose an algorithm to compute equilibrium payments between banks in a network of interbank debt liabilities. The algorithm follows chains of defaults and stops when no further default is induced by the previous ones. More recent papers consider other types of financial contracts between banks, such as equity claims (Elliott et al. 2014). These claims make the market values of banks interdependent as well: A drop in a bank's portfolio depresses its own value, which then depresses the value of its equity holders, that of their equity holders, and so on.[9] Such models have been extended to include both debt and equity (e.g., Jackson & Pernoud 2019). Equity-like interdependencies have different implications for systemic risk than debt contracts, as they enable banks to contribute to contagion without defaulting. For example, Bank 1's drop in value, even if the bank is solvent, can depress Bank 2's value if Bank 2 holds shares of Bank 1's stock, and this can drive it to insolvency and cause it to incur bankruptcy costs. This can precipitate defaults among Bank 2's creditors, especially if they were already weak from holding Bank 1's stock. Thus, combinations of drops in equity value, defaults on debt, and common exposures can lead to cascades of defaults.

Inefficiency arises here from the externality that an institution's investment decision affects the returns to others' portfolios and the institution's ability to pay its debts in ways that cannot be completely hedged by those affected. These are not simple transfers of value from one institution to another, given that insolvency involves bankruptcy and other costs.

2.2.2. Correlated investments, fire sales, and other exposures in common. Another form of contagion, less direct, comes from externalities in asset prices. When a bank becomes insolvent, it often has to sell prematurely significant amounts of assets in so-called fire sales. Such dumping depresses prices for those assets, reducing the portfolio values of other banks holding similar assets. This can lead other banks to default and drive their asset sales into a downward spiral (Kiyotaki & Moore 1997, Cifuentes et al. 2005, Gai & Kapadia 2010, Capponi & Larsson 2015, Greenwood et al. 2015). This is particularly problematic when portfolios are correlated across banks. That leads both to more danger from the exposures across banks at the same time and to greater pressures on prices in the resulting fire sales.

The effect of fire sales on market prices depends on several market imperfections. One is that the financial market is not deep enough to absorb a liquidation of a large bank's portfolio without

[9]There is evidence that such equity-like cross-holdings generate systemic risk. For instance, investment funds increasingly invest in each other, and these cross-holdings have become a major source of vulnerability (Fricke & Wilke 2020).

a price impact. There may also be asymmetric information, and market participants may infer something about underlying fundamentals when observing large-scale sales. A decrease in market prices can thus amplify an initial shock, especially in a financial system in which many assets are marked to market and there are asymmetries in information and large institutions.

Importantly, price-based contagion due to commonalities in exposures across banks can worsen the cascades of insolvencies. Here we see a three-level interaction between two counterparties that have similar exposures in their investments. First, they both tend to be vulnerable and near insolvency at the same time. Second, if one is forced to sell off some of its assets, then the price effect can hurt the other's balance sheet. Third, if then one defaults on the other, the latter can become insolvent, especially in light of the first two interactions, which mean that this bank is already distressed. Combined, these three effects can lead to cascades when the direct default impact, the common exposure, or the indirect price impact would not have led to further insolvencies by themselves. For example, Cifuentes et al. (2005) and Gai & Kapadia (2010) show via simulations how contagion due to counterparty risk can be amplified by fire sales. They consider financial networks that allow for two types of linkages between banks: (*a*) balance sheet obligations and (*b*) price effects whenever a bank is forced to deleverage its portfolio. They then study how the risk of contagion depends on the network structure of interbank obligations, and in particular on its density.[10] This is not just a theoretical concern, as there is evidence that two banks are more likely to be counterparties if their portfolios are more correlated (Elliott et al. 2018), suggesting that banks that are connected via financial obligations also tend to be more connected via commonalities in exposures.

2.2.3. Indirect inferences. Commonalities in exposures pave the way for another form of contagion: guilt by similarity. People have doubts about the solvency of other enterprises that are similar to an insolvent one.[11] Two key elements make such contagion possible: (*a*) correlated portfolios across banks and (*b*) uncertainty about the value of fundamentals and/or the banks' portfolio structures.

To illustrate these ideas, consider $k = 1, \ldots, K$ primitive assets, with independent values p_k. A bank's portfolio is solely characterized by its investment in the different assets $q_i = (q_{ik})_k$. To isolate the inference effect, suppose that banks have no contracts with each other: The entire value of each bank is based on the bank's own portfolio of primitive assets. The (undirected) financial network in this example captures correlation in asset holdings such that $g_{ij} = \sum_k q_{ik}q_{jk}\sigma_k^2$, with $\sigma_k^2 = \mathrm{Var}(p_k)$. Even if investors cannot directly observe the realized values of the different assets or the portfolios of the banks—so they are unsure about either the q_i's or the p_k's or both—the market values of banks in equilibrium should still be consistent and satisfy

$$V_i = F_i(\mathbf{V} \mid \mathbf{G}) = \mathbb{E}\left[\sum_k q_{ik}p_k \mid V_{-i}\right] \quad \text{for all } i.$$

Consider once more the network in **Figure 1**, and let there be two outside assets with returns p_A and p_B, respectively. First, suppose that Bank 2's entire portfolio is invested in asset A, that

[10]For the sake of simplicity, both papers assume that if one bank is forced to abruptly sell assets, the adverse effect on others' balance sheets is the same for all the other banks. How the interaction between these two networks affects the risk of contagion under more general network structures remains a broadly open question.
[11]Readers are referred, e.g., to King & Wadhwani (1990), Acharya & Yorulmazer (2008), Caballero & Simsek (2013), Alvarez & Barlevy (2015), and Stellian et al. (2021). Diebold & Yılmaz (2014) provide a more general background on the comovement of firms' values and on network positions.

Bank 1's portfolio is split equally between the two assets, and that this is known to investors. Ex ante, without any additional information, the value of each bank simply equals the unconditional expected value of its portfolio: $V_1 = \mathbb{E}[0.5(p_A + p_B)] = 0.5(\mu_A + \mu_B)$ and $V_2 = \mu_A$. Now consider what happens if it is revealed that Bank 1's value will be lower than expected, that is, $0.5(p_A + p_B) = X < 0.5(\mu_A + \mu_B)$. Then, given the overlap in asset holdings, investors should update their valuation of Bank 2 as well to $V_2 = \mu_A - 2\sigma_A^2(\sigma_A^2 + \sigma_B^2)^{-1}[0.5(p_A + p_B) - X] < \mu_A$.

As a variation, suppose that $p_A = 0$ and $p_B = 1$ is known, and instead the correlation comes from the fact that investors believe the two banks hold the same portfolio—so they know that $q_1 = q_2$ but not those values. Then, if they see that $V_1 = 0.5$, they infer that $V_2 = 0.5$. These correlations induce what we call inference-based contagion: Upon observing a decrease in the value of Bank 1, investors make inferences about other banks' values due to the correlation in portfolios (the source of the externality), in terms of both structure and payoffs, across banks. With imperfect knowledge of those portfolios, they make inferences that could end up being justified ex post or not. This form of inference-based contagion is made worse by the fact that banks are part of a complex financial network, whose structure is imperfectly known. Caballero & Simsek (2013) show that the complexity of the network of interbank cross-exposures can lead risk-averse banks to take the prudential action more often than what is efficient and to pull back funding from one another when a negative shock hits.

These different types of externalities and interconnections interact, and a firm might be vulnerable in one network (e.g., inference from some other failure) and then cause a cascade into another (e.g., default on its payments). Thus, proper evaluation of systemic risk requires a holistic view of the different types of interdependencies between institutions.[12]

2.3. Multiple Equilibria and Self-Fulfilling Feedback Effects

Systemic risk can arise even in the absence of any change in fundamental values. As soon as a financial network allows for multiple equilibria, a mere shift in beliefs can move the system discontinuously from one equilibrium to another, with real economic consequences. Belief changes could arise from inferences, as mentioned above, that reflect real underlying correlations; but they could also arise via sunspots, bubbles, or exogenous events that can be conditioned upon by investors (see, e.g., Shell 1989, Reinhart & Rogoff 2009). The key idea is that if there are multiple equilibria, then which equilibrium applies depends on which one people expect.

2.3.1. Panics and runs. The classic form of bank runs and panics falls under the category of systemic risk defined by self-fulfilling behavior. This source of risk stems from banks' primitive role of transforming short-term deposits into long-term illiquid investments, which makes banks inherently fragile institutions: If enough depositors withdraw their funding before the bank realizes its investments, the bank cannot repay all of them and defaults. Classic treatments of this range from Keynes's (1936) to Diamond & Dybvig's (1983), and they show that by merely expecting a bank to be insolvent and by withdrawing their deposits, depositors can induce its insolvency (for more background, see Reinhart & Rogoff 2009). Importantly, this sort of risk need not be triggered by a decrease in the value of the bank's fundamentals, but merely by a shift in beliefs about the health of the institution. It could even be that people know that a bank is healthy but are

[12]For more background on interconnected networks, readers are referred to Kivela et al. (2014), Burkholz et al. (2016), Garas (2016), and Atkisson et al. (2020).

worried that others are unsure of its health.[13] The inefficiency here comes from the externality that returns on investment for a depositor depend on the behavior of other depositors. This complementarity in investments leads to the existence of multiple equilibria, as people's expectations about how assets will be valued can come to be self-fulfilling—and fear becomes contagious.[14] This holds even for an isolated bank, and hence even in the absence of any interdependencies between financial institutions.[15]

2.3.2. Credit freezes. Fear and pulling back of investments can occur not only on the part of depositors and outside investors but also on the part of banks. Uncertainty about economic conditions can lead banks to doubt how sound many businesses will be. This can feed on itself, because if banks fear a recession they can pull back their capital and require ever higher interest rates. This can lead to defaults, and banks may begin to doubt each other's health and to stop contracting with each other, making it more difficult for banks to rebalance their portfolios. This leads to further tightening and potential spiraling, and possibly to a complete credit freeze. Again, this sort of freeze can be self-fulfilling:[16] The lack of investment worsens the conditions of businesses and financial intermediaries, which makes them worse investments, which then justifies the pullback (Bebchuk & Goldstein 2011); and thus this can be a problem even if no changes in fundamentals drive the beliefs. This was present in the freeze of overnight lending between 2007 and 2009 (e.g., see the discussion in Brunnermeier 2009, Diamond & Rajan 2011.) Not only did lending dry up, but also many stock markets around the world lost nearly half or more of their values (e.g., in the case of the Dow), while the underlying fundamentals did not reflect such a dramatic drop. Central banks had to provide much of the liquidity in interbank loan markets.

2.3.3. Self-fulfilling defaults. Financial contracts between banks can lead to self-fulfilling chains of defaults. Recall that interbank contracts make bank values interdependent. The anticipation of one bank failing to pay its debts can depress the value of other banks and feed back to the original bank, making its default self-fulfilling. In this case there are externalities in terms of both payments and inferences. As a simple example, consider the same model of interbank claims introduced in the Section 2.2.1 above and the network depicted in **Figure 2**. For the sake of the example, suppose that neither bank has any outside assets, that they each owe $D_{12} = D_{21} = 1$ to the other, and that the recovery rate on a defaulting bank's assets is zero. If one of the banks, say Bank 1, pays back its debt to the other, then Bank 2 has enough capital to pay its debt in full as well. Bank 1 is then indeed able to repay Bank 2: Such repayment is self-fulfilling, and there exists an equilibrium in which both banks remain solvent and $V_1 = V_2 = 0$. There exists, however, another equilibrium in which both banks default and $V_1 = V_2 = -1$. Indeed, if Bank 1 expects

[13] Of course, one can take this up to further levels of beliefs: People might know the bank is healthy and know that others know that the bank is healthy, but they might not know whether others know that everyone thinks the bank is healthy, and so on (Morris & Shin 2002, Allen et al. 2006).

[14] In some circumstances, one can refine the uncertainty and produce unique predictions of self-fulfilling runs, as done by Morris & Shin (1998); but uncertainty about which equilibrium will be played can also be problematic, as in Roukny et al.'s (2018) work.

[15] Non-depository institutions can also face similar liquidity risk: For instance, broker-dealers can face runs from their collateral providers (Infante & Vardoulakis 2018).

[16] The literature mostly highlights the self-fulfilling, spiraling nature of credit freezes, which is the reason we mention it in this section, but such behavior on the part of banks can also amplify the effect of a shock and hence contribute to the first type of systemic risk. For instance, a bank hit by a liquidity shortfall may need to withdraw (or equivalently refuse to roll over) its loan to another bank to meet its payments, and this bank may then be forced to call in its loans to others as well, and so on. An initially small liquidity shortfall can thus spread and lead to a broader liquidity crisis (Gai et al. 2011).

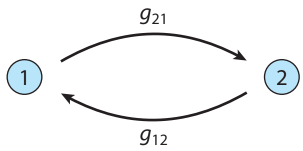

Figure 2

A ring network with two banks. The arrows point in the direction in which the value of claims flows.

not to have its claim on Bank 2 paid back, it cannot pay back its own debt, and vice versa. Obviously, this example is trivial in the sense that the two banks should just cancel out each others' debts. However, in more complicated cycles, especially ones with different forms of contracts and differing maturities, such cancellation can be difficult to identify and execute.

This example shows how self-fulfilling default cascades differ from classic bank runs, as they are generated by network interdependencies rather than purely by beliefs. They appear in any network of exposures between banks for which there are multiple equilibrium values for interbank claims (e.g., Elliott et al. 2014, Roukny et al. 2018, Jackson & Pernoud 2020). When there are costs associated with bankruptcy, such cascades are not simply failed transfers but trigger real economic costs, and this multiplicity of equilibria has efficiency consequences.

2.3.4. Fire sales and contract renegotiations. We close this section by highlighting that commonalities in asset holdings and fire sales can also generate multiple equilibria and hence a self-fulfilling worsening of the financial system. Consider, for instance, two banks holding the same asset, and suppose that the value of the asset drops if a bank sells large quantities of it. This could be due either to a lack of sufficient market depth or to inferences if there is uncertainty about why the asset is being sold. In normal times, if neither of the banks is forced to sell its holdings, the value of the asset remains high: There is an equilibrium with high bank values in which they both remain solvent. There is also another equilibrium in which they both dump a significant portion of their holdings, which depresses the price of the assets and hence the values of the banks. This is self-fulfilling if one bank liquidating its holdings has a strong-enough price impact to force the other to do so as well. This appears in the investment model of Krishnamurthy (2010), where multiple equilibria can coexist and exhibit various degrees of liquidation and price levels. Caballero & Simsek (2013) consider a model that incorporates both dominos due to cross-exposures between banks and fire sales. They show that there can exist both an equilibrium in which contagion is contained and prices remain fair, and another in which banks take prudential actions, leading to fire sales, low market prices, and worse contagion.[17]

Fire sales are not the only way in which the deterioration of banks' balance sheets is exacerbated during stressed times. So far we have taken obligations between banks as fixed, but they are inherently dynamic and evolving. If a bank is expected to face low returns, and as a result to be close to defaulting, then others will require greater collateral when extending credit to it. This worsens the situation of the bank and can even precipitate its default, making it self-fulfilling.[18]

Naturally, all these forms of systemic risk interact and are often at play at the same time.[19]

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[17]Malherbe (2014) highlights the role of adverse selection in generating self-fulfilling liquidity dry-ups.
[18]Fostel & Geanakoplos (2008, 2014) provide more background on the leverage cycle, analyzing how much collateral is required on loans and studying how it feeds back into asset prices in equilibrium.
[19]Siebenbrunner (2021) discusses an approach to quantifying the relative contributions of different forces to systemic risk.

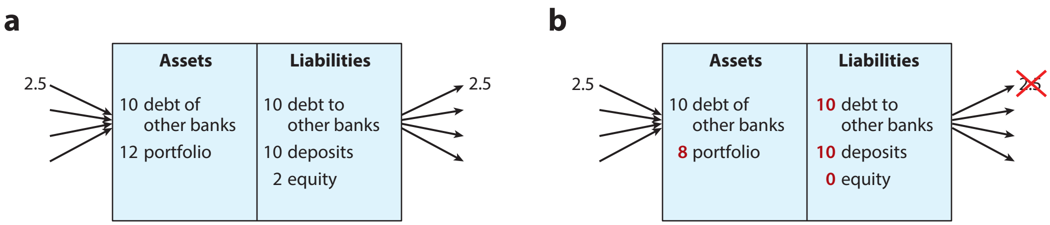

Figure 3

(*a*) The starting balance sheet of the banks in a network. (*b*) Some bank's portfolio drops to a value below 10, e.g., to 8. This makes the bank insolvent, and so the bank defaults on some of its payments.

3. NETWORK STRUCTURE AND SYSTEMIC RISK

We now discuss how network structure affects systemic risk. Because much of the literature on this question is based on networks of obligations between banks, we mostly restrict our attention to interdependencies based on interbank contracts.

We first discuss how drops in equity values and defaults on debt can cascade, and how such cascades depend on the structure of the network and the type of shock. We then discuss systemic risk stemming from self-fulfilling feedbacks and elaborate on the kinds of network patterns that generate such feedbacks.

3.1. Non-monotonicities in Network Density

Countervailing forces in financial networks lead contagion to be non-monotonic in network density. This is a point studied in detail by Elliott et al. (2014), and it applies to a variety of models, including those by Cifuentes et al. (2005), Gai & Kapadia (2010), Wagner (2010), Elliott et al. (2014), Gofman (2017), and Jackson & Pernoud (2019). This distinguishes contagion in financial markets from, for instance, transmission of a disease or diffusion of an idea, for which adding more interactions only leads to more extensive rates of spreading.[20]

As a bank adds counterparties, it becomes susceptible to drops in values or defaults from more sources, which tends to increase the potential for cascades. However, holding a bank's total exposure constant, spreading that exposure over more counterparties makes the bank less exposed to any given counterparty, which lowers the potential for contagion. To study these two forces, Elliott et al. (2014) distinguish two basic dimensions of the interconnectivity between financial institutions: (*a*) how many partners each institution has, which they call the density of the network; and (*b*) the fraction of a bank's portfolio held in contracts with other institutions, which they call the integration of the network.

We illustrate the non-monotonicity of these two forces in the context of a simple example. Consider a network of identical banks that have balance sheets of the form shown in **Figure 3*a***.

[20]This also goes beyond what is known as complex contagion, that is, contagion of something that takes several interactions to lead to infection—that requires, for instance, hearing a rumor several times before believing it and passing it along, or following the actions of a majority of friends [see Centola (2018) and Jackson (2019) for background discussion and references, and Jackson & Storms (2017) for a detailed look at how complex contagion varies with network structure]. Financial networks have elements of complex contagion, since a bank may only become insolvent after several counterparties default, but also have non-monotonicities in how many interactions they have.

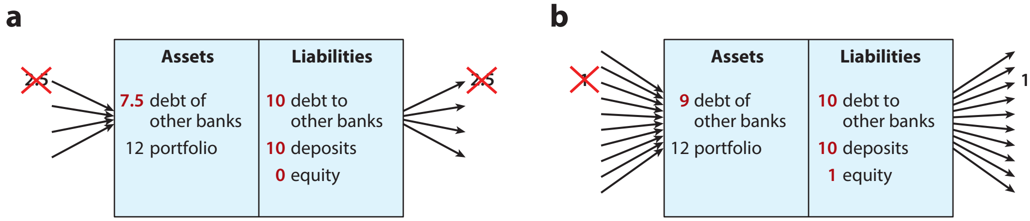

Figure 4

(*a*) A second bank now becomes insolvent due to its lost asset value from the loan to the first bank. It then defaults on some of its payments. (*b*) Even though banks have more counterparties, the lower exposure to each one of them now makes them immune to a default by any single counterparty.

On the liability side, each bank has 10 units of capital from deposits and another 10 units of capital from loans from other banks, and the banks' owners have 2 units of capital in the form of equity. On the asset side, each bank has an investment portfolio worth 12 and loans to other banks worth 10.

In this example, we can measure the level of integration as 10—which is how much of the bank's assets comes from other banks, in this case in the form of interbank debt. The density for this bank is 4, counting the number of counterparties the bank has. So these levels of integration and density lead to an exposure of 2.5 per counterparty. In this example, the bank also owes 2.5 to each of four counterparties, so that there is a full symmetry.

Now let us suppose that the investment portfolio of one of these banks drops in value, as in **Figure 3*b***. This bank is now insolvent, and so it defaults on some of its payments. For the purposes of this example, let us treat the default as total on at least one of its loans, due to bankruptcy costs, although one can obviously extend the example to work with some partial default.

Initially the bank owed four different banks 2.5, and so it fails to make at least one of these payments. This has to be written off by the counterparty that made the loan to the first bank, and so that second bank loses 2.5 of its assets. The second bank is now insolvent as well and defaults on some of its payments. Again, let us presume bankruptcy costs so that the bank fails to pay any of at least one of its loans, as pictured in **Figure 4*a***. This now cascades.

With an exposure of 2.5 to each other bank, and an initial equity value of only 2, banks are susceptible to even a single defaulting counterparty. Both the level of integration and the density of the network in this example are important in driving the defaults. If the banks had lower levels of integration but the same density, their exposure to any given counterparty would be less than 2.5, and if it was less than 2, then no single counterparty's default could erase a bank's equity value. Increasing the integration—i.e., the amount of exposure of each bank to others—tends to increase the propensity for contagion, as it does in this example.[21]

Similarly, if a bank still had an integration level of 10 but had greater density (i.e., more partners), so that it had exposure of no more than 2 to any single counterparty, then the cascade would also be avoided. To see the importance of density, let us alter the example so that each bank has 10 counterparties and owes 1 unit to each, as in **Figure 4*b***. Therefore, the level of integration is

[21]However, as Elliott et al. (2014) also discuss, increasing integration can help diversify a given bank's portfolio by changing the assets that the bank is implicitly holding through its connections, depending on the circumstances. Thus, more exposure can help diversify any given bank's portfolio, making its investments less variable and more stable, but also leads to an increase in the possibility of contagion.

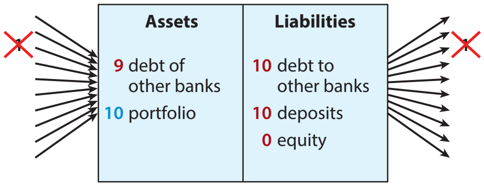

Figure 5

With correlated portfolios, banks are now more susceptible to the defaults of others, even when their levels of exposure to any single counterparty are low. This can undo the benefits of diversification and non-monotonicity discussed in the text, and now a second bank can default even if it has 10 partners.

the same, but the density has increased. In this case, there is no longer any cascade. The default by any single counterparty no longer leads a bank to become insolvent.

Here we see the non-monotonicity quite clearly. We have increased the number of counterparties of each bank, and hence have made the financial network denser, and yet we have eliminated the cascade. Contagion is non-monotonic since if we started with no counterparties, then there would not be any contagion. Or, if we just had two banks, each paired to the other, then one would drag the other down, but the effects would not spread. The case with four counterparties hits a sweet spot: The density is high enough to lead to a very connected network where things can spread widely, and each bank is exposed enough to others that a single default can trigger an insolvency in a counterparty. Once we increase up to 10 counterparties, then a single default is no longer a major problem for any single counterparty.

Correlation in portfolios can mitigate and even erase this non-monotonicity in contagion by removing gains from diversification and increasing common vulnerabilities. To illustrate the role of correlation, reconsider the example above (see **Figure 4**). Suppose that banks' portfolios exhibit substantial correlation—perhaps because they all have substantial exposure to the same sort of collateralized debt obligations, as was the case in 2007. For example, suppose that when one bank's portfolio drops below 10, the portfolios of other banks are also likely to be at below-normal levels. If we change the portfolio of the second bank pictured in **Figure 4*b*** to drop to 10 at the same time as the first bank's portfolio drops to 8, then the default of the first bank is enough to push the second bank into insolvency—as pictured in **Figure 5**. In addition, the asset sides of banks' balance sheets are further depressed not only due to the fact that their portfolios are weak at the same time, but also because more than one of the debts that they are owed are defaulted upon at once due to the correlation in other banks' values.[22]

One way to understand this effect is that positive correlation in investments across banks erases some of the benefits of diversification in counterparties and facilitates contagion. More generally, increasing the correlation in portfolios of investments leads to increased probabilities of codefaults. For example, Wagner (2010) considers two banks and two assets and makes the observation that if both banks fully diversify their portfolios by equally dividing it between the two assets, their portfolios end up being perfectly correlated. Hence there exists a trade-off in that more diversification—which comes hand in hand with more correlation between banks' portfolios—reduces the unconditional probability that each bank defaults but can push up the probability that they default together (presuming they were invested in different assets to begin with), hence increasing systemic risk. Of course, the worst case is the one in which the banks have similar and

[22]For other examples and simulations of the impact of correlated portfolios on systemic risk, readers are referred to the online appendix of Elliott et al. (2014).

underdiversified portfolios—for instance, they all hold similar mortgages or loans—as the portfolios are then correlated and risky.

3.2. Robust Yet Fragile

As stated by Haldane (2009), and studied in detail by Gai & Kapadia (2010), financial networks have the intriguing property of being "robust yet fragile."[23] Interdependencies between banks, in the form of lending or liquidity provisions, for instance, allow for risk sharing, which can help individual institutions be less susceptible to individual liquidity or portfolio shocks. Those shocks are spread among counterparties, and this sort of diversification helps lower the chance of any individual institution's failure. This is the sense in which financial networks are robust. However, very large shocks can cause an institution to fail despite the diversification, and then interdependencies can transmit the shock more widely and more extensively. There are, of course, nuances in this that depend on the model and the type of contracts that exist between institutions (see, e.g., Allen & Gale 2000, Gale & Kariv 2007, Gai & Kapadia 2010, Battistoni et al. 2012, Elliott et al. 2014, Acemoglu et al. 2015a).

This is related to the non-monotonicity discussed above, but it is a distinct phenomenon. The robust-yet-fragile property means that one network can be an improvement over another in some situations but can also make things much worse in others. In the above discussion of non-monotonicity, we considered how changes in the network affect whether or not a particular shock cascades—therefore, the comparative static was in the network holding the shock constant. The robust-yet-fragile phenomenon is instead a comparison of how a given network fares against different types of shocks.

Acemoglu et al. (2015a) focus on networks of unsecured interbank debt and study how a shock to a bank's returns propagates through the network. They distinguish between two shock regimes: shocks that are small enough to be absorbed by total excess liquidity in the system and shocks that are not. In the former regime, interdependencies unambiguously alleviate the risk of contagion: The network structure most resilient to contagion is the complete network, in which each bank's total liabilities are spread equally across all other banks. This leads to maximal risk sharing and minimal expected number of defaults. However, if shocks are larger than the total excess liquidity in the system, interdependencies just facilitate their propagation. One can see a foreshadowing of this point in the analysis of Allen & Gale (2000), which shows, in a more specific setting, that the risk of contagion depends on whether there is aggregate uncertainty about the demand for liquidity. If not, interbank connections increase risk sharing without generating systemic risk.

Cabrales et al. (2017) highlight the role of the size of shocks in a different model in which interdependencies between banks capture the correlations in their investments. They consider a set of ex-ante identical banks, each having debt due to outsiders and access to a risky project. Returns to these projects are subject to shocks that are identically and independently distributed across banks. If a bank is unable to cover its debt to outsiders, it defaults and incurs some costs due to distress. Banks have the possibility of diversifying their portfolio by exchanging claims on each other's projects: The link from i to j captures the claim that bank i has on the return of j's project. Hence, linkages in their model represent correlation in portfolios across banks and not any sort of interbank obligation. The same trade-off emerges: More links allow for better risk sharing but also entail being exposed to more sources of risk. The network structure leading to the least expected number of defaults depends on the distribution of shocks. In particular, Cabrales et al.

[23] Callaway et al. (2000) offer an earlier discussion of percolation on graphs and such a trade-off.

(2017) show that if large shocks are likely, then the empty network is optimal. If shocks are mostly small, then the complete symmetric network is the most resilient. Other shock distributions can lead intermediate network density to minimize contagion.

Acemoglu et al. (2015a) characterize the network structures most or least resilient to contagion under different shock regimes. If shocks are small, the complete network leads to the lowest risk of contagion. In contrast, the ring network, in which each bank's claim is concentrated on a single counterparty, is the structure most prone to contagion. The analysis applies to regular networks, in which all banks have as many interbank claims as liabilities and have the same number of counterparties. This rules out heterogeneity in bank size and in connectedness, as well as the possibility that a bank will be a net lender or borrower.

Generally, analytic tractability limits full characterizations to such simple settings. An alternative is to use the properties of large random networks. Each technique offers valuable insights and tractability but applies to limited classes of networks.

A challenge is that financial networks often involve significant asymmetries—such as the presence of a core-periphery structure—and that affects the risk of contagion. Large core banks can be resistant to small shocks but can fail catastrophically when hit with large shocks, especially when those shocks are correlated. This matters, as shown, for instance, by Elliott et al. (2014), who use simulations to document how core-periphery networks can also erase some aspects of the non-monotonicity discussed in Section 3.1, since the failure of a large bank or entity to which core banks have large exposure can lead to extensive contagion within the core and then spread to the whole system. This was what loomed in 2008. There are also other studies that provide evidence that heterogeneity makes a substantial difference. For instance, Gai et al. (2011) provide simulations showing that contagion varies with the level of concentration in networks of interbank claims; Glasserman & Young (2015) provide some theoretical results showing that contagion is the largest when banks are heterogenous in size and the shock originates at a large central bank, in a certain class of networks; and Teteryatnikova (2014) shows how a negative correlation between neighboring banks' degrees (i.e., numbers of counterparties) can help make the network more resilient.

Given the complexity involved, it makes sense to continue our analyses in two directions, developing more insights into how the structure of heterogeneity matters in financial contagion as well as specific applications to provide more empirical background on features of networks that are prevalent and relevant. Another direction is to apply models of contagion to observed networks for the simulation of risk patterns, an approach increasingly used by regulatory institutions (Aikman et al. 2009, Basel Comm. Bank. Superv. 2015).

3.3. Self-Fulfilling Feedback Effects and Freezes: The Role of Cycles

Next, we discuss how network structures matter for the second type of systemic risk: self-fulfilling feedbacks that generate multiple equilibria.

A burgeoning literature has highlighted the role of cycles in generating multiple equilibria (see Roukny et al. 2018, D'Errico & Roukny 2019, Jackson & Pernoud 2020), as was previewed in **Figure 2**. In a network of interbank obligations, cycles enhance counterparty risk without creating value in the financial system; clearing cycles hence reduce the risk of default cascades without affecting the values of banks. For example, Roukny et al. (2018) show that there exist multiple equilibria for bank values if and only if there is a cycle composed of banks that are sufficiently interconnected, such that a bank's solvency depends on the solvency of its predecessor in the cycle.

As an illustration, consider the financial networks depicted in **Figure 6**. In the network in **Figure 6*a***, if no bank pays its debt, then given that each bank's portfolio value of 10 is less than

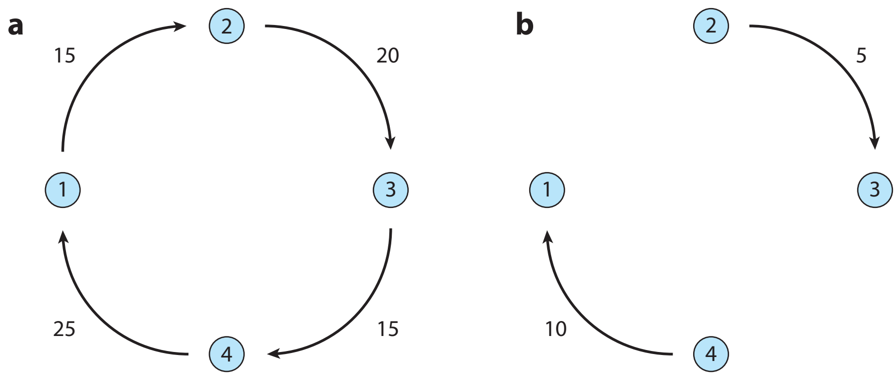

Figure 6

Both networks in panels *a* and *b* have the same net debts, but one has a cycle and the other does not. All banks have portfolios worth 10. If a bank becomes insolvent, it pays none of its debt. In the network in panel *b*, there is a unique equilibrium in which all banks are solvent. In the network in panel *a* there are two equilibria: one in which all banks are insolvent and default, and the other in which no bank defaults.

the debt the bank owes, no bank can afford to pay its debt. This becomes self-fulfilling: There is an equilibrium in which all banks are insolvent and no debts are paid. There is also an equilibrium in which all debts are paid. In contrast, in the network in **Figure 6*b***, the gross debts have been netted out and only net debts remain. There is then a unique equilibrium in which all banks are solvent. Clearing all cycles eliminates the possibility of multiple equilibria and ensures that only the best equilibrium remains. Thus, there can be large gains from clearing cycles, especially if one expects banks, and investors more broadly, to hold pessimistic beliefs—or to believe that others hold pessimistic beliefs.

Of course, this example is stylized to make it clear how banks could net out their debts and avoid the bad equilibrium. However, in practice these cycles are much more complex, involving many banks, different debt maturities or contract types, and other factors that can lead to inertia and make such a coordination failure more likely, especially if times are uncertain and people delay payments on debts. Thus, it is important to understand when cycles can be problematic and how to overcome them when they exist.

Jackson & Pernoud (2020) study self-fulfilling cascades and freezes in detail and characterize how they rely on the presence of cycles, the portfolios of the banks, and the costs and delays involved in insolvencies.[24] Such self-fulfilling cascades and freezes become less likely if some banks have lower gross exposures, as these banks may then have enough capital to act as buffers and stop the cascade. Self-fulfilling cascades occur whenever no bank on a given cycle has enough assets coming from outside the cycle to spark a repayment cascade in that cycle. Jackson & Pernoud (2020) also allow for more general financial contracts between banks and characterize the existence of multiple equilibria, showing that they are generated by a particular type of cycle involving some debts but potentially other contracts, too. However, they show that cyclical structures that do not involve some key debt obligations cannot lead to multiple equilibria. This characterization of the cyclical structures of a network not only explains equilibrium multiplicity and freezes but also provides the basis for identifying the minimum bailouts needed to return a network to full solvency, as discussed below.

[24]In the absence of bankruptcy costs, bank values are generically unique (Eisenberg & Noe 2001).

Gains associated with clearing cycles can provide some insight into the use of a risk management technique called portfolio compression (D'Errico & Roukny 2019). This technique consists in a netting mechanism that aims at reducing gross interbank exposures, and hence regulatory requirements. A similar intuition is often put forward when discussing the benefits from clearing bilateral over-the-counter (OTC) trades through central clearing counterparties (CCPs). CCPs allow for multilateral netting of interbank contracts, which enhances transparency of the financial network and limits counterparty risk.[25] If interbank contracts are restricted to debt contracts, such multilateral netting boils down to clearing cycles, as shown in **Figure 6**.

4. INCENTIVES IN FINANCIAL NETWORKS

Systemic risk depends on several factors—including network structure, the portfolios of institutions, and their correlation—that are endogenous: These result from choices by the institutions that compose the network. Thus, it is vital to understand whether institutions have efficient incentives, that is, incentives to make investments and choose partnerships that maximize the overall value of the financial system.

Given that financial networks are full of externalities, we should expect individual financial incentives to fail to align with the overall welfare of the economy. Indeed, the literature shows that incentives are misaligned on many dimensions. We start by reviewing how interconnections between banks, and the associated potential for contagion, affect banks' investment decisions in outside assets. We then look at banks' incentives when choosing their interbank assets and how these impact the equilibrium network structure.

4.1. Investment Decisions

The literature has highlighted two main distortions in banks' investment decisions: They have an incentive to take on too much risk and to excessively correlate their portfolios with those of their counterparties. We discuss how the network structure comes into play in both of these inefficiencies.

4.1.1. Inefficiently risky investments. There are two main ways in which financial interdependencies can lead banks to take on too much risk compared to what is socially optimal, and they relate to the two types of systemic risk identified in Section 2.

First, a bank's investment decisions affect not only the bank's own value but also, indirectly, the values of its counterparties, and of its counterparties' counterparties, and so on. This sort of externality is not new to the financial network setting: There are many settings in which the choice of investments might not reflect the interests of all those who are affected (Admati & Hellwig 2013), with an early illustration of this being offered by Jensen & Meckling (1976) in which a manager makes choices that do not reflect the shareholders' interests. This has been investigated in a variety of network settings (Brusco & Castiglionesi 2007, Hirshleifer & Teoh 2009, Galeotti & Ghiglino 2021, Jackson & Pernoud 2019, Shu 2019), where the externalities are wide and the interests extend well beyond those directly interacting with an institution.

As an illustration, Jackson & Pernoud (2019) consider the following portfolio choice problem, in which each bank i has access to a safe asset with constant rate of return $1 + r$ and to a risky

[25] Readers are referred to Duffie & Zhu (2011) for more detailed discussion and background and to Capponi & Cheng (2018) and Wang et al. (2020) for more recent papers on the design of margin and collateral requirements for CCPs.

asset with random return $\tilde{p}_i$, with $\mathbb{E}[p_i] > 1 + r$. Banks are furthermore linked to each other via financial contracts that take the form of either debt or equity. Fully investing in the risky asset is a strictly dominant strategy for a bank as soon as the bank does not belong to a certain type of cycle in the network, even though this can result in excess systemic risk. Intuitively, only specific cycles generate the possibility that the bank's risky behavior may feed back to itself through the network by triggering a default cascade. Without the risk of such feedback, banks overlook any external costs they trigger when weighting the benefits and costs of a riskier investment, which can lead them to overinvest in the risky asset.

Second, network interdependencies can make a variety of banks' decisions strategic complements, leading to socially inefficient outcomes. For example, Allouch & Jalloul (2018) consider a network of interbank liabilities in which banks have the possibility of storing part of their initial cash flow to overcome any future net deficit, instead of cashing out these benefits right away at the cost of foregone future returns. They show that this can be viewed as a coordination game in which banks choose either default or no default. Banks' decisions are strategic complements, since it is easier for a bank to remain solvent if other banks remain solvent as well. They show that, if there are cycles of debt in the network, there can exist bad equilibria in which banks choose to cash out early and then default because they expect others to do so as well. These equilibria are inefficient as all banks, as well as their outside creditors, would have been better off had they all coordinated on remaining solvent.

4.1.2. Endogenous correlation of investments. There are many forces that push financial institutions to correlate their investments. Some are basic herding forces: Seeing others make an investment may signal something about that investment's prospects (Banerjee 1992, Bikhchandani et al. 1992, Chincarini 2012), or the people who are choosing investments may worry about their reputations (Scharfstein & Stein 1990). Other forces pushing toward correlation are regulations that limit the scope of investments, essentially pushing banks to hold certain classes of assets or minimum amounts of certain assets, or to have a portfolio that meets certain risk characteristics. Banks also have forces that push them into the same lending strategies as their competitors (e.g., Cohen-Cole et al. 2015). Though the aim of such regulations is to make portfolios safer, the fact that they push banks to hold similar assets can make rare negative shocks (e.g., a major sovereign default) hit many institutions at the same time.

Beyond these forces, there are also network forces. A first aspect of importance is the incentive of the regulator when deciding whether to bail out insolvent banks. If more banks fail at once, a default cascade is more likely to be triggered, and the regulator has more incentives to step in. Acharya & Yorulmazer (2007) highlight this too-many-to-fail problem that incentivizes banks to correlate their portfolios, because if they all become insolvent together then they are all more likely to be rescued. Another driving force of banks' incentive to herd is the risk of information contagion, which we described in Section 2. In a world of incomplete information, adverse information on some banks can increase the borrowing costs of others, because investors negatively update about the creditworthiness of the latter. Such inferences make it less valuable to have an uncorrelated portfolio and, as Acharya & Yorulmazer (2008) show, banks prefer to have correlated investments. Yet another force is detailed by Elliott et al. (2018), who consider a model in which banks can swap claims on each other's investments in order to hedge shocks to their exposures. There are no interbank liabilities, but each bank owes some debt to outside investors. Because shareholders act under limited liability, they have an incentive to shift losses from them to debt holders. Such risk shifting motivates banks to correlate their portfolio returns, such that if one is hit by a large shock others are too, they all default, and losses are born by creditors. Finally, in a model that accommodates debt and equity claims between banks, Jackson & Pernoud

(2019) show how incentives depend upon counterparties' portfolios. All else equal, a bank prefers to be solvent when it earns the most returns from its contracts with other banks. This pushes it to prefer to be solvent when others are solvent and insolvent when others are insolvent. This leads perfect correlation of portfolios across counterparties to be an equilibrium, and in fact to be the Pareto-dominant equilibrium from the banks' shareholders' perspective.

Private party monitoring and reputations can also help mitigate incentive issues, as poor investments raise the capital costs of financial institutions (Godlewski et al. 2012, Godlewski & Sanditov 2018). This can affect banks' choices of portfolios and partners in the network. Although dynamics can help mitigate some problems, moral hazard problems are generally not extinguished by reputations and monitoring (e.g., Diamond 1991, Rajan 1992, Holmstrom & Tirole 1997). How banks' incentives are affected by such feedbacks in financial networks is an important open topic.

4.2. Incentives in Network Formation

We now review what is known about banks' incentives when choosing their counterparties in the financial network, and we highlight inefficiencies. Inefficient network formation is a recurring theme in the literature, starting with Jackson & Wolinsky's (1996) work, but it plays out in particular ways in the context of financial institutions.

Several factors can lead a core-periphery structure—empirically observed in many financial markets—to arise endogenously, and some of these factors are based on the various roles of core banks as intermediaries in financial markets. Babus & Hu (2017) show that when partnerships between banks have not only a trading function but also an informational function, then there are economies of scale in intermediation and the equilibrium network has a star structure. The central agent has information about all others, enforces all contracts, and ends up intermediating all trades at some fee. Because the star network leads all relevant information to be centralized, it is constrained efficient. Farboodi (2017) examines settings in which it is not information frictions that drive intermediation, but banks' unequal access to investment opportunities. Banks that have access to these opportunities constitute the core, and funds flow to them from the periphery. The equilibrium network is socially inefficient—core banks overconnect whereas periphery banks underconnect—and the core captures intermediation rents. Finally, as Wang (2017) shows, a core-periphery structure can also stem from inventory economies of scale. In a market in which institutions have random trading needs, intermediaries can arise to complete those trades. This leads to random inventories for the intermediaries, and thus concentrated intermediation reduces inventory risk via a law of large numbers. This trades off against the market power of intermediaries. As Wang shows, this leads to a socially inefficient equilibrium network, with either too few or too many dealers (core banks) depending on the asset's trading frequency.

Beyond core-periphery structures, the number of counterparties a bank chooses can generate inefficiencies in itself, as it affects systemic risk, which is less than fully internalized by banks. Acemoglu et al. (2015b) show that banks tend to lend too much to each other and spread their lending insufficiently across borrowing banks. This underdiversification of interbank liabilities appears despite the fact that equilibrium interest rates reflect the risk-taking behavior of borrowers: Bilateral externalities are internalized via equilibrium interest rates, but not the more general network externality, leading the equilibrium network to be socially inefficient. Similarly, an analysis by Jackson & Pernoud (2019) shows that banks tend to choose too few counterparties on which to hold claims, because they overlook the contagion costs others incur when they go bankrupt.[26]

[26]The incentives can also depend on the structure of the contract and on bargaining between counterparties, as shown by Duffie & Wang (2016).

Furthermore, the equilibrium network exhibits homophily in portfolios of outside assets (Elliott et al. 2018): Banks prefer to be counterparties of other banks that have similar portfolios. This is the flip side of choosing portfolios that are correlated with those of one's counterparties. When choosing on whom to hold claims, banks acting under limited liability undervalue diversification and prefer to be linked to banks with similar portfolios. This implies that, when a shock hits, banks default together and shift losses to debt holders.

Inefficiency is not the only prediction of the literature on financial network formation. Some papers document forces that drive the formation of networks that avoid widespread contagion. In particular, Babus (2016) shows that if banks can commit to mutually insure each other against liquidity shocks, then there exist equilibria in which contagion never occurs. Erol & Vohra (2018) consider networks that are stable to deviations by groups of banks that can restructure their connections and sever outside ones. In their model, a bank defaults as soon as one of its counterparties does so; therefore, if any bank in a component defaults, all will. Given a positive benefit from forming a connection, each bank should connect to all other banks that it already has a path to. This leads to the prediction that a stable network will be a collection of fully connected disjoint clusters. Group stability ensures that the number of banks in each cluster will be the one that maximizes their overall value. Although empirically observed networks have much more heterogeneity, the reasoning behind Erol & Vohra's (2018) results can help explain why the core in core-periphery networks is often fully connected.

Finally, fear of contagion can lead to credit freezes, whereby banks abstain from lending to each other, resulting in an overly sparse network. Acemoglu et al. (2020) discuss how the extent of a credit freeze depends on the structure of the underlying network of potential partnerships between banks and the distribution of liquidity shocks. They show how the financial system may fail to allocate capital efficiently from depositors to entrepreneurs due to intermediation frictions.

5. REGULATION AND INTERVENTION

We now turn to issues surrounding regulation by a government authority that is interested in overall societal welfare and understands the systemic risks and inefficiencies discussed above.

5.1. The Necessity of Network Information

As should be obvious by now, properly addressing systemic risk requires a holistic view of the network.[27] Let us illustrate some reasons underlying the importance of seeing details of the network in order to assess which are the key institutions to regulate and/or bailout.

An important component of systemic risk assessment is stress testing, which is usually run in a decentralized manner. The main input into many stress tests is balance sheet data, which describe the amount of each type of financial asset and liability held by each bank. Depending on the jurisdiction, balance sheet data do not always provide complete, or even partial, information about one's counterparties and hence about the network structure. Such local data can completely

[27]Attempting to assess systemic risk without detailed network information is what Jackson (2019) refers to as "flying jets without instruments," that is, operating a complex interactive system without the necessary measurements. Even though some measures that work without network information (e.g., S-risk) may correlate with more precise full network measures, if they are only approximately capturing the real risks, they can be ineffective.

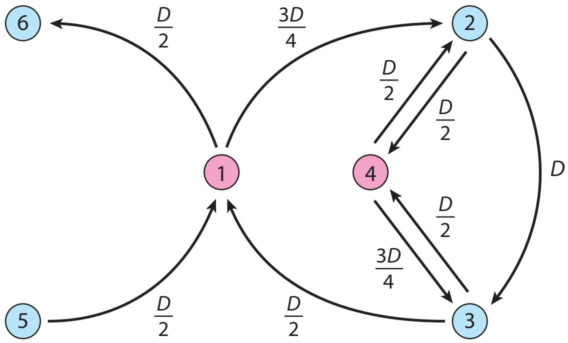

Figure 7

The arrows point in the direction that a debt is owed. Bank 1 and Bank 4 (*magenta*) have the same balance sheet: They both have two debt claims on other banks (both of $D/2$) and two debt liabilities (one of $D/2$ and one of $3D/4$). They are both net debtors.

miss which banks are most likely to start a default cascade or be caught up in one. This point is straightforward but worth emphasizing given its importance.

For ease of illustration, consider a network in which banks are linked only via debt contracts. A measure of systemic risk based on local balance sheet information depends only on the face value of each bank's assets and liabilities and not on the identities of its counterparties. To show why this is insufficient information, we give an example of a financial network in which two banks have identical balance sheets, and yet their defaults have significantly different consequences. Hence, if the central authority were able to bail out one (and only one) of the two institutions, it could not make an optimal decision based on local information.

In particular, consider the network depicted in **Figure 7**. Suppose the portfolios of Bank 1 and Bank 4 both yield 0, so that they are both insolvent. Let Bank 2 earn a return on its portfolio that falls between $3D/4$ and D, and let Bank 3 earn a return below $D/4$ and Bank 5 a return above $D/2$. Let the recovery rate on assets of a defaulting bank be zero. Despite the fact that Bank 1 and Bank 4 have the same balance sheet, only the former induces widespread default contagion if it remains insolvent. Indeed, Bank 2 and Bank 3 have enough buffer to absorb the shock of Bank 4's default, but not that of Bank 1's. Hence, bailing out Bank 1 prevents the whole system from insolvency, while bailing out Bank 4 does not change anything and a full systemic failure occurs.

This example also highlights the fact that, without network information, one cannot even identify which banks are at risk of insolvency. For instance, if one examines the books of Bank 3 without knowing that Bank 2 is exposed to Bank 1, then even if one knows the portfolio realizations of Bank 3's counterparties but does not know the looming failure of Bank 1, it will appear that Bank 3 is free from danger of insolvency. Although this is a simple example, it illustrates why regulatory agencies that cannot see parts of the network (e.g., foreign institutions, shadow banks, etc.), or have data only from local stress tests, are disadvantaged.

Accordingly, and partly spurred by the lessons learned from the 2008 financial crisis, assessments of systemic risk that involve nontrivial portions of the network are beginning to emerge. For example, the European Central Bank has information on the counterparties involved in the largest exposures of most banks within its jurisdiction. This permits the construction of a network consisting of a portion of the assets and liabilities within the European banking sector and some pointers to banks outside of Europe. Accordingly, some calculations of systemic risk of a nontrivial part of the network are beginning to emerge (e.g., see Covi et al. 2019, Farmer et al. 2020). Similarly, the Bank of England has regulatory data on bilateral transactions between UK banks, allowing for the analysis of the UK interbank network in different asset classes (see Ferrara et al. 2017, Bardoscia et al. 2018). This is an important advance in the assessment of systemic risk, but much more is needed, especially outside of Europe and for the growing shadow banking system, which falls outside of most jurisdictions.

5.2. Addressing Systemic Risk

With some network information in hand, and an understanding of the issues discussed above, we can think about optimal interventions in financial markets. We discuss this in two parts: one about avoiding cascades and the other about avoiding bad equilibria and feedbacks in settings with multiple potential outcomes. Let us start with the second one.

5.2.1. Eliminating self-fulfilling feedbacks. The literature has brought forward several ways a regulator can intervene to address systemic risk stemming from multiple equilibria and self-fulfilling crises. Such crises are the consequence of a coordination problem between some agents taking part in financial markets. For instance, a bank run arises when depositors mis-coordinate and all withdraw their deposits, and a credit freeze occurs when banks all choose to abstain from lending. Importantly, in both of these cases, there exists another equilibrium in which no crisis occurs and which is preferred by all. One way to eliminate this source of systemic fragility is to have the regulator insure all lending, either via deposit insurance (Diamond & Dybvig 1983) or by committing to be the lender of last resort and inject capital whenever necessary (Bebchuk & Goldstein 2011, Diamond & Rajan 2011). If credible, this eliminates the possibility of mis-coordination.

Self-fulfilling crises due to coordination failures differ from contagions triggered by fundamental losses in that self-fulfilling crises can be stopped at no capital cost to the regulator. This is a key distinction between the two types of systemic risk. By guaranteeing deposits or lending, a regulator ensures that no bank run or credit freeze will lead banks to default, and hence the regulator will not have to intervene in equilibrium.

Even if a regulator does not insure interbank lending ex ante, and a self-fulfilling default cascade or freeze occurs (**Figure 2**), the cascade or freeze can still be ended by injecting (at least partially recoverable) capital in the network appropriately. Jackson & Pernoud (2020) show that such cascades stem from the presence of cycles of claims in the network, and that stopping them requires injecting enough capital to clear these cycles. The injection of capital is a way of jump-starting the payment cycle, avoiding a bad equilibrium. They also show that any capital injected into self-fulfilling cycles can be fully recouped by the regulator, making this part of the bailout policy virtually costless. To illustrate this, reconsider the network of **Figure *6a***. If someone, for example, injects 5 units of capital into either Bank 1 or Bank 3, there is a unique equilibrium in which all banks are solvent: Bank 1 can pay Bank 2 (even without any inflow from Bank 4), which can then pay Bank 3, and so on. Moreover, that capital can then be recovered by the injecting authority once all debts are paid. In contrast, note that injecting 5 units of capital into Bank 2 or Bank 4 would not have the same effect: The bad "all default" equilibrium would still exist. More generally, as Jackson & Pernoud (2020) show, there are key banks that are most advantageous to inject capital into in order to ensure that only the best equilibrium remains, and this depends on the leverage that their payments provide in the network. This can also depend on which banks lie on multiple cycles at once, which happens in more complex networks. Jackson & Pernoud (2020) characterize the minimal injections of capital needed to restore solvency and show that finding the least expensive approach is a complex (NP-hard) problem when many banks are involved. However, they also show that in some well-structured networks, such as core-periphery networks with some symmetries in the sizes of banks and balance sheets within the core, finding optimal bailout policies is more straightforward and intuitive.

Another solution that has been brought forward to avoid mis-coordination and self-fulfilling crises is to have all transactions go through a CCP. Centralization helps because it allows for multilateral nettings of obligations, which in particular eliminates cycles of claims and reduces the possibility of multiple equilibria. Csóka & Herings (2018) highlight the gains from centralization when clearing payments between banks. They show that a centralized clearing process always yields the best equilibrium for bank values, whereas a decentralized process converges to the worst equilibrium.

Of course, these interventions may distort banks' investment incentives ex ante, leading them to take on even more risks, and may be socially costly in that sense. We discuss the interplay between regulation and incentives in Section 5.3.

5.2.2. Ex-ante reserves or capital requirements versus ex-post bailouts.

As discussed in Section 2.2, an initial loss by some financial institution can get amplified by network interdependencies and spread through the financial system. The ensuing bankruptcy costs are real losses to the economy and can be avoided, or at least minimized, by intervention.

There are two main ways in which a regulator can intervene that have been considered. One is to regulate banks ex ante so as to ensure that inefficiently risky investments are avoided. This can be done via various forms of prudential regulation, for instance, by imposing reserve, liquidity, or capital requirements;[28] constraining the types of investments that different institutions can make; and monitoring banks' capital ratios and investments on an ad hoc basis. A second way is to allow arbitrary investments but then intervene and inject capital if some danger of cascading default arises, in order to minimize contagion. As shown by Jackson & Pernoud (2019), whether one wants to intervene depends on the financial centrality (more on that below) of the bank in question.[29] If a bank is sufficiently central so that it poses substantial systemic risk, then whether it is better to regulate it ex ante or bail it out ex post depends on the relative opportunity costs of the excess returns lost by forcing the bank to hold safer assets compared to the real costs of a bailout.[30,31]

The determination of which financial institutions contribute the most to systemic risk can be made using notions of financial centrality. The literature has suggested several measures of centrality, aiming to assess either the exposure of a given bank to systemic risk or how much the bank itself contributes to it.[32] Some of these measures are solely based on market data on the portfolio returns of individual banks, and they include features of contagion through either fire sales (Duarte & Eisenbach 2018, Engle & Ruan 2019) or the correlation structure of returns between bank portfolios (Billio et al. 2012). Other measures are based on the underlying network of interbank contracts and rely on models of contagion via counterparty risk (Amini et al. 2016, Hauton

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[28]Martínez et al. (2020) discuss the differences between various capital and liquidity requirements and how their effects depend on bank size and business cycles. Also, such policies interact across jurisdictions, and, for instance, Karamysheva & Seregina (2020) show that prudential policies have substantial spillovers in risk reduction across countries.

[29]Readers are referred to Belhaj et al. (2020) for further discussion of centrality and prudential regulation.

[30]Readers are referred to Lucas (2019) for an estimate of bailout costs in the 2008 financial crisis.

[31]There are further issues to be considered. For example, when bailing out a bank, one can do so by providing capital with some hopes that it will be repaid in the future. Providing that capital in the form of debt can end up merely changing the timing of the default, whereas offering bailout money in an equity form avoids imposing additional constraints on the payments the distressed institution has to make.

[32]Paying attention to centrality makes more of a difference in asymmetric networks, such as core-periphery ones, compared to more regular networks (see, e.g., Capponi & Chen 2015).

& Héam 2016, Jackson & Pernoud 2019). For example, Jackson & Pernoud (2019) propose a measure of a bank's financial centrality based on its systemic impact when fundamental asset prices go from p to p'. Given a network of interbank contracts and liabilities, one can trace how this change will cascade through the network and affect the solvencies and values of all institutions. By seeing how the change in a given bank's portfolio cascades, one can assess its systemic importance. This measures the eventual total change in the value accruing to all outside investors in the financial system.

From another perspective, Demange (2016) proposes a measure of spillover effects in a network of interbank liabilities that relies on the properties of equilibrium debt payments between banks. She defines an institution's threat index as the marginal impact of an increase in its direct asset holdings on total debt repayments in the system. This index is null for all institutions that are solvent, as they are already able to pay back their debt in full. The index is strictly positive for defaulting institutions, as a larger portfolio means that they can repay a larger fraction of their liabilities, which may enable other banks to repay more of their liabilities, and so on. The extent to which this spreads through the network is then captured by the institution's threat index. This can be viewed as a marginal version of the measure above, where marginal refers to changes that are small enough not to change any of the defaults but the payment streams.

Public bailouts come at a cost to the regulator, and in particular they can depress the price of government bonds when they are financed by debt. If banks hold large amounts of sovereign debt, this further worsens the value of their portfolios, and even larger bailouts are required to maintain their solvency. This "doom loop" was a key contributor to the sovereign debt crisis in Europe following the Great Recession. Capponi et al. (2020) propose a model incorporating this amplification mechanism and characterize optimal bailouts in this setting.

All these papers focus on networks of financial organizations, but a regulator should be interested in the impact on the overall economy. Contagion is indeed not specific to financial markets: For instance, the structures of input-output networks and supply chains can induce small shocks to magnify in a similar manner as a financial network can amplify shocks to returns and affect asset prices (e.g., Acemoglu et al. 2012, Barrot & Sauvagnat 2016, Ramírez 2017, Herskovic 2018). Determining the optimal injection of capital, then, requires a good understanding of the interplay between financial networks and supply chains, which is a topic that has not yet received a lot of attention.

5.3. Feedback Between Regulation and Markets

The previous section considered interventions to address systemic risk but took as given the network and portfolios. Of course, these are endogenous, and changes in regulation can affect them. This interplay between regulation and the incentives of market participants is only partly understood. Accounting for responses to regulation can change some comparative statics and policy implications.

5.3.1. Regulation and investment incentives. Regulation that aims at reducing systemic risk can have perverse effects on banks' investment incentives.

For example, bailouts, if anticipated, can lead to moral hazard, as banks no longer suffer the costs of risky investments.[33] The mechanism through which this works is nuanced, since the

Supplemental Material >

[33]This can even happen with private bailouts, as shown by Elliott et al. (2014) (see the **Supplemental Appendix**). A bank that knows it will be bailed out by another bank in the event of insolvency can have incentives to make riskier choices as it bears less of the consequences of those insolvencies.

shareholders who control a bank may not gain value during a bailout, whereas debt holders would. However, there are a variety of reasons the management of a bank may wish to avoid insolvency that have nothing to do with equity value. There is evidence that this matters; for instance, Dam & Koetter (2012) find that bailouts led German banks to take on more risk. Similarly, Calomiris & Jaremski (2019) look at the effect of the introduction of deposit insurance in the United States in the early nineteenth century. They find that deposit insurance reduced market discipline and led to more risk taking on the part of banks. Hence, reducing liquidity risk came at the cost of a higher risk of insolvency, because of the induced distortion of banks' incentives. Public bailouts affect not only banks' investment decisions but also their choices of counterparties, and hence the equilibrium structure of the financial network (Erol 2019). Without bailouts, a network with high clustering and low concentration endogenously arises in response to the possibility of counterparty (and more importantly, second-order counterparty) risk. The anticipation of bailouts, however, makes banks less concerned about contagion risk, introducing a network hazard that leads to low clustering and high concentration in the equilibrium network. This perverse effect of bailouts adds to the more standard moral hazard problem they induce.

At present, there is little empirical work on how the structure of the financial network responds to changes in regulation. A notable exception is a recent study by Anderson et al. (2019) that looks at the effect of the National Banking Acts of 1863–1864 on the topology of the US banking system. The National Banking Acts established reserve and capital requirements and created a reserve hierarchy. This led the banking system to become more concentrated around a few core banks, located in designated reserve cities. This allowed for better diversification but increased the potential for contagion if one of the core banks were to fail.

5.3.2. Public bailouts, private bail-ins, and counterparty choice. Given the high financial cost of public bailouts and the perverse incentives they generate, attention has been paid to private-sector resolutions of defaults, especially since the last financial crisis. Private-sector bail-ins—i.e., private banks rescuing each other when insolvent—can be incentivized, and such incentives depend on the topology of the financial network. It can be in one bank's interest to rescue another if the gains from preventing its default are higher than the costs of rescue. Gains come from the value of interbank assets, which are enhanced if a default cascade is prevented. This means that linkages between banks not only spread shocks but also incentivize private-sector bailouts, so that a more interconnected financial system can reduce systemic risk and lead to more investments (Leitner 2005). Kanik (2019) shows how bankruptcy costs induce private-sector bailouts, as they magnify losses due to defaults.[34] He examines the incentives of coalitions acting together to avoid defaults and shows that nonclustered networks with intermediate levels of interdependencies lead to optimal incentives. Furthermore, if the network is clustered, potential losses are not fully internalized by solvent banks, leading to inefficient rescue levels.

The incentives can be complex, as many different entities all gain from avoiding defaults. For example, Bernard et al. (2017) analyze the interplay between public bailouts and private bail-ins. Bail-ins can only be incentivized if the regulator can credibly commit to not step in, which is only the case when contagion in the absence of intervention is limited enough. For large enough shocks, interconnectedness makes it in the regulator's interest to step in if no one else does, and then bail-ins cannot be incentivized. Furthermore, banks contribute to a bail-in if and only if they get a high enough share of the induced gains, which generally diffuse through the entire financial

[34]In settings without any bankruptcy costs, incentives can completely disappear, as shown by Rogers & Veraart (2013).

system. Hence, the more diversified a network is, the less individual banks are willing to step in and rescue each other.

5.3.3. Shadow banking and moving targets. One important and problematic characteristic of financial networks is their complexity, which can make them opaque.[35] Financial markets involve many different types of market participants who are trading various kinds of financial assets, leading to complex and multidimensional interconnections. Moreover, part of this complexity arises in response to regulation, with financial innovations and new products being introduced to circumvent regulatory restrictions (Silber 1983).[36] Importantly, a significant portion of these trades are realized in OTC markets and hence may be known only to the two parties directly involved in the exchange, when not required to be disclosed. In the absence of full network data, one can design policies that are optimal in the face of uncertainty about the structure of the network and the costs of improving transparency, which is a new direction explored by Ramírez (2019).

Even if one has detailed accounting information from all of the financial institutions within some regulatory jurisdiction, the difficulty of monitoring the financial network is aggravated by the increasingly large portion of the financial system that operates outside the jurisdiction of financial regulation, which makes it even harder for regulators to have a complete picture of the market. In addition, the shadow banking system is endogenous and can expand in response to stricter restrictions in the regulated system. This was, for instance, one of the side effects of Regulation Q of the 1933 Glass–Steagall Act, which prevented banks from paying interests on checking accounts. When interest rates increased in the 1950s, this left room for the emergence of substitute forms of demand deposits that paid interest—e.g., savings and loans, and money market deposit accounts—leading investors to move their capitals to the shadow banking system (Lucas 2013). Once those were regulated, new forms of unregulated institutions emerged, and the variety of institutions that are involved in some sort of financial intermediation is now quite enormous.

Taking a step back, it is far from clear what the scope of financial regulation should even be. Where should the regulator draw the line between institutions that are are considered to be financial ones, and are regulated as such, and those that are not? Take, for instance, large corporations, such as private universities with large endowments. They are often both borrowing and lending at the same time, interacting with both the financial system and the real economy. In a similar manner as more traditional banks, they can spread shocks and take part in financial contagion: Should they be regulated in a similar way?

5.4. Political Challenges

As should be clear from our discussion above, regulation is far from being of a one-size-fits-all kind, and optimal intervention depends on many factors, including network positions and centralities that are constantly shifting. Unfortunately, regulations are slow to adjust and are often constrained by politics, since intervention can benefit some parties more than others. Historically, regulation surged after financial crises (e.g., the Glass–Steagall Act and the Dodd–Frank Act) and

[35]In addition, the financial organizations involved may be concerned about keeping information about their trading positions and partners private. Hastings et al. (2020) discuss some related issues as well as new methods of obtaining critical network information while preserving privacy.

[36]Anderson et al. (2020) show how growth in shadow banking interacts with interventions within the banking sector and can exacerbate risk.

then slowly eroded over time until another crisis hit.[37] The discretion granted to central banks and other regulators is one way of avoiding political cycles, but even that discretion changes with time. In fact, that discretion can often be unclear, as was true in the 2008 crisis during which it was not obvious how much authority the Treasury and the Federal Reserve had to intervene directly. Building a regulatory system that quickly adjusts to constantly shifting financial networks is yet another challenge.

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The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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