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 and firesales), 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.

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“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. In addition, the financial sector is characterized by strong interdependencies - so capital is not only circulating 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, have 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 US and elsewhere, and to a broad financial crisis and prolonged recession.

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 which 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 their partners; and 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. 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 term “systemic risk.”

Many forms of systemic risk can be mitigated or even avoided altogether via appropriate

1See Lund & Harle (2017).
2For narratives of the crisis see the US Congressional Financial Crisis Inquiry Report of January 2011, as well as Glasserman & Young (2016) and Jackson (2019).
3We do not directly address the issue of bubbles in this survey, but one can find extensive treatment elsewhere (e.g., Shiller (2015)).
oversight and judicious intervention. However, this requires a detailed view of financial interdependencies, 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. It is an ideal time to provide a conceptual framework within which we can organize the main insights. In what follows, we draw a distinction between two types of systemic risk: (i) contagion through various channels that generate externalities among financial institutions (e.g., defaults, correlated portfolios, and firesales), and (ii) self-fulfilling prophecies and feedback effects (e.g., bank runs, credit freezes, equilibrium multiplicity). 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 Online Appendix, along with an executive summary of this survey.

2 A Taxonomy of Systemic Risk in Financial Networks

Defaults and financial crises are as old as investment: from the immense credit crunch under the emperor Tiberius in 33CE, to the repeated external defaults by most countries involved in the Napoleonic wars, and 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 (i) contagion through direct externalities (e.g., when a default by one bank leads to distress for another, or a firesale of one bank’s assets depresses the value of another bank) and (ii) 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 require-

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4For detailed overviews of the broader networks literature see Jackson (2008, 2019). References on financial networks appear in an early review by Summer (2013), and references to more recent papers appear throughout this survey. Chapter 4 of Jackson (2019) details a financial crisis and discusses some key aspects of financial markets and policy prescriptions.
ments; 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 lead their values to be correlated. 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 interdependencies 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 that of $j$, given induced shifts in trades and prices.

Although the nature of the financial network varies across models, they 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 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 all the institutions in the financial system whose actions affect others.

The network is characterized by a matrix $G = (g_{ij})_{i,j}$ such that $g_{ij}$ captures the connection between bank $i$ and $j$. A connection $g_{ij}$ can have multiple components, for instance each corresponding to a different type of financial contract.\(^5\)

A key object of interest is the vector of values associated with each institution, $V = (V_i)_i$, 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 others’ values, denoted by $V_i = F_i(V \mid G)$. Banks’ values are then the solution to a system of $n$ equations in $n$ unknowns, written as:

$$V = F(V \mid G).$$  \hfill (1)

Under some conditions – in particular that $F(\cdot \mid G)$ is nondecreasing and bounded in $V^\uparrow$ – Tarski’s fixed point theorem applies, and there exists an “equilibrium”: values, consistent with each other, that solve (1). So, 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

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\(^5\)Thus, it may be a multigraph; or one can think of it as multiplexed - so layered networks. The different types of contracts can interact, as shown by Bardoscia et al. (2017) for UK bank data.

\(^6\)That is, if $V'_i \geq V_i$ for all $i$, then $F(V' \mid G) \geq F(V \mid G)$, and also that the set of feasible $V$’s is bounded above and below.
institutions simultaneously, which we call the “best” and “worst” equilibria in what follows.\footnote{The best and worst equilibria can be found via a simple algorithm: Start with the maximum possible values \( V^{\text{max}} \) (or minimum to find the worst) and then iteratively apply the function \( F \). In many financial models, the convergence is fast (e.g., see \cite{EisenbergNoe2001, JacksonPernoud2020}) as the base asset values drive the equations, while with more arbitrary interdependencies, finding the equilibria can be much slower (e.g., see \cite{EtessamiEtAl2019}).}

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 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 a 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 \( V \) change in response to some initial change in fundamentals, while keeping the equilibrium being considered constant – whereas the second type of systemic risk captures shifts between equilibria.\footnote{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 \cite{AllenGale2007}. In the former crises are driven by changes in fundamentals, whereas the latter are self-fulfilling prophecies that can be triggered solely via beliefs and behaviors.}

A contagion-based crisis is triggered by a change in fundamentals, whereas what triggers an equilibrium shift can be more nebulous and is less well-understood. In the context of financial networks, an equilibrium shift can 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 generating inefficiencies.

### 2.2 Contagion Through Network Interdependencies

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

**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, this worsens the balance sheets of other institutions 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 2-bank relationship depicted in Figure\(^1\) and let it represent a debt claim: \( g_{ij} \) indicates that \( j \) owes a debt \( D_{ij} \) to \( i \) - so arrows point in the direction in which value should flow. In this example \( g_{ij} = D_{ij} \). Interbank contracts generate interdependencies between banks’ (book) values:

\[
V_i = F_i(V \mid G) = \pi_i + \sum_j (d_{ij}(V) - D_{ji}),
\]
where $\pi_i$ is the value of bank $i$’s portfolio of ‘outside’ investments\footnote{These are investments that are not in other financial institutions, such as mortgages, loans to non-financial companies, equity, etc.} and $d_{ij}(V)$ the amount $j$ can manage to pay to $i$. Because of limited liability, the value of this debt equals

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

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

![Figure 1: Bank $j$ owes a debt of size $g_{ij}$ to $i$.](image)

To see how interdependencies generate systemic risk, let $D_{ij} = 1$, $\pi_i = .5$ and suppose that $j$’s outside portfolio value drops from $\pi_j = 1.5$ to $\pi_j' = .5$. Bank values start at $V_i = 1.5, V_j = .5$ under $\pi$, but under $\pi'$ fall down to $V_i = 1$ and $V_j = -.5$ (or effectively 0 given limited liability). Though the shock only affected the portfolio of bank $j$, it also depressed 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 it ignores the fact that insolvencies involve substantial bankruptcy costs. For instance, an extra .5 in bankruptcy costs would lead to $V_i = .5$ and $V_j = -1$ under $\pi'$. Each 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 Rochet & Tirole (1996); Allen & Gale (2000), and 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 hits several banks, or when the network is not appropriately connected. Then, liquidity drawn by one bank from another can spillover and 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, Golub & Jackson (2014)). These claims make market values of bank interdependent as well: a drop in one’s
portfolio depresses its own value, which then depresses the value of its equity holders, and their equity holders’, etc. Such models have been extended to include both debt and equity (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 solvent, can depress Bank 2’s value if it holds shares of 1’s stock, and that can drive it to insolvency and 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 its ability to pay its debts in ways that cannot be completely hedged by those affected. These are not simply transfers of value from one institution to another given that insolvency involves bankruptcy and other costs.

**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 “fire sales”. Such dumping depresses prices for those assets, reducing the portfolio values of other banks holding similar assets. This can lead others to default, and their assets sales to create a downward spiral (Kiyotaki & Moore (1997); Cifuentes, Ferrucci & Shin (2005); Gai & Kapadia (2010); Greenwood, Landier & Thesmar (2015); Capponi & Larsson (2015)). This is particularly problematic when portfolios are correlated across banks. That leads both to stronger exposures, and greater pressures on prices in 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 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, there are asymmetries in information, and large institutions.

Importantly, price-based contagion due commonalities in exposures across banks can worsen cascades of insolvencies. Here we see a three-level interaction between two counterparties who 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 it can lead the second to become insolvent, especially in light of the first two interactions which mean that it is already distressed. Combined, these three effects can lead to cascades when either the direct default impact, common exposure, or 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.

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10 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)).
sales. They consider financial networks that allow for two types of linkages between banks: balance-sheet obligations, as well as price effects whenever a bank is forced to de-leverage its portfolio. They then study how the risk of contagion depends on the network structure of interbank obligations, and in particular its density. This is not just a theoretical concern, as there is evidence that two banks are much more likely to be counterparties if their portfolios are more correlated, suggesting that banks that are connected via financial obligations also tend to be more connected via commonalities in exposures.

**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. Two key elements make such contagion possible: correlated portfolios across banks and 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: all of their value is based on their 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 $\sigma_k^2 = \text{Var}(p_k)$. 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 $q_i$s or the $p_k$s or both – the market values of banks in equilibrium should still be consistent and satisfy

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

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 bank 1’s 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: $0.5(p_A + p_B) = X < 0.5(\mu_A + \mu_B)$. 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 $V_1 = .5$, they infer $V_2 = .5$.

These correlations induce what we call “inference-based contagion:” upon observing a de-

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11For 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.

12For instance, see King & Wadhwani (1990); Acharya & Yorulmazer (2008); Caballero & Simsek (2013); Alvarez & Barlevy (2015); Stellian, Penagos & Danna-Buitrago (2020). For more general background on co-movement of firms’ values as well as network positions, see Diebold & Yilmaz (2014).
crease in the value of Bank 1, investors make inferences about other banks’ values due to the correlation in portfolios (the source of the externality), both in terms of 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., then default on its payments). Thus, proper evaluation of systemic risk requires a holistic view of the different types of interdependencies between institutions.

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 (Shell (1989)), bubbles, or exogenous events that can be conditioned upon by investors. The key idea is that if there are multiple equilibria, then which equilibrium applies depends on which one people expect.

Panics, and Runs. The classic form of bank runs and panics falls under this category of systemic risk, in which behavior becomes self-fulfilling. 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 (1936) to Diamond & Dybvig (1983) and show that by merely expecting a bank to be insolvent and withdrawing their deposits, depositors can induce its insolvency. 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 worried that others are unsure of its health. 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

\[13\text{For more background on interconnected networks see Kivela et al. (2014); Burkholz et al. (2016); Garas (2010); Atkisson et al. (2020).}\]

\[14\text{For more background see Reinhart & Rogoff (2009).}\]

\[15\text{Of course, one can take this up to further levels of beliefs: people might know the bank is healthy, and know that others know that the bank is healthy, but not know whether others know that everyone thinks the bank is healthy, etc. (Allen, Morris & Shin (2006); Morris & Shin (2002)).}\]
be valued can come to be self-fulfilling - and fear becomes contagious. This holds even for an isolated bank, and hence even in the absence of any interdependencies between financial institutions.

**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, as if banks fear a recession they can pull back their capital and require ever higher interest rates. This can lead to defaults, and banks to 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 spiralling, and possibly to a complete credit freeze. Again, this sort of freeze can be self-fulfilling; the lack of investment worsens the conditions of businesses and financial intermediaries, making them worse investments, which then justifies the pullback; 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 many stock markets around the world lost nearly half or more of their value (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.

**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 feedback to the original bank, making its default self-fulfilling. Here we have externalities both in terms of payments and inferences. As a simple example, consider the same model of interbank claims introduced in the section on cascades of insolvencies above, and the network depicted in Figure 2. For the sake of the example suppose 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 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 \( V_1 = V_2 = -1 \).

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16 In some circumstances, one can refine the uncertainty and produce unique predictions of self-fulfilling runs, as in [Morris & Shin, 1998]; but uncertainty about which equilibrium will be played can also be problematic as in [Roukny, Battiston & Stiglitz, 2018].

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

18 The literature mostly highlights the self-fulfilling, spiraling nature of credit freezes, which is why 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 as well. 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, which may then be forced to call in its loans to others as well, etc. An initially small liquidity shortfall can thus spread and lead to a broader liquidity crisis (Gai et al, 2011).
Indeed, if Bank 1 expects not to have its claim on 2 paid back, then 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 just transfers failing to be made, but trigger real economic costs, and this multiplicity of equilibria has efficiency consequences.

**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 to either a lack of sufficient market depth, or from 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 asset, 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.\footnote{See also Malherbe (2014), who highlights the role of adverse selection in generating self-fulfilling liquidity dry-ups.}

Fire sales are not the only way in which the deterioration of banks’ balance sheets is exacer-
bated during stressed times. So far we have taken obligations between banks as fixed, but they are inherently dynamic and evolve. If a bank is expected to face low returns, and as a result of being 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.\footnote{See Fostel & Geanakoplos (2008, 2014) for more background on the leverage cycle, which analyzes how much collateral is required on loans and studies how it feeds back into asset prices in equilibrium.}

Naturally, all these forms of systemic risk interact and are often at play at the same time.\footnote{Siebenbrunner (2020) discusses an approach to quantifying the relative contributions of different forces to systemic risk.}

3 Network Structure and Systemic Risk

We now discuss how network structure affects systemic risk. Since, much of the literature on this question is based on networks of obligations between banks; we mostly restrict 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. Second, we discuss how this type of contagion via counterparty risk is affected by additional interdependencies between banks stemming from correlated investments. Third, we discuss systemic risk stemming from self-fulfilling feedbacks and 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 nonmonotonic in network density. This is a point studied in detail by Elliott, Golub & Jackson (2014), and it applies to a variety of models including Cifuentes, Ferrucci & Shin (2005); Gai & Kapadia (2010); Wagner (2010); Elliott, Golub & Jackson (2014); Gofman (2017); Jackson & Pernoud (2019). This distinguishes contagion in financial markets from, for instance contagion of a disease or diffusion of an idea, for which adding more interactions only leads to more extensive rates of spreading.\footnote{This also goes beyond what is known as ‘complex contagion’: contagion of something that takes several interactions to lead to infection – 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 (2015) 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 counter-parties default, but also have nonmonotonicities in how many interactions they have.}

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 it less exposed to any given counterparty, which lowers the potential for contagion. To study these two forces, Elliott, Golub & Jackson (2014) distinguish two basic dimensions of the interconnectivity between financial institutions: how many partners each institution has, which they call the...
“density” of the network; and the fraction of a bank’s portfolio held in contracts with other institutions, which they call the “integration” of the network.

We illustrate the nonmonotonicity of these two forces in the context of a simple example. Consider a network of identical banks that have balance sheets of the form in Figure 3 (Left).

![Figure 3](65x508 to 547x630)

**Figure 3**: (Left) The starting balance sheet of the banks in a network. (Right) Some bank’s portfolio drops to a value below 10, say to 8. This makes the bank insolvent, and so it defaults on some of its payments.

On the liability side, each bank has 10 units of capital from deposits, another 10 units of capital from loans from other banks, and their 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 those 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 (Right). 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 then 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 it fails to pay any of at least one of its loans, as pictured in Figure 4 (Left). This now cascades.

With the 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.\footnote{However, as Elliott, Golub & Jackson (2014) also discuss, increasing integration can help diversify a given bank’s portfolio by changing the assets which it is implicitly holding through its connections – depending on the circumstances. Thus, more exposure can help diversify any given bank’s portfolio, making their own investments less variable and more stable, but also leads to an increase in the possibility of contagion.}

Similarly, if a bank still had an integration level of 10, but greater density (more partners) so that it had exposure of no more than 2 to any single counterparty, then the cascade would also have been avoided.

To see the importance of density, let us alter the example so that each bank has 10 counterparties to which it owes 1 unit each, as in Figure 4 (Right). So, the level of integration is 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 nonmonotonicity quite clearly. We have increased the number of counterparties of each bank, and hence made the financial network denser, and yet have eliminated the cascade. It is nonmonotonic since if we started with no counterparties, then there would not have been any contagion. Or, if we just had two banks each paired to each other, then one would have dragged the other down, but it would not have 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 ten 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 introduced above (Figure 4). Suppose 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

Figure 4: (Left) 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. (Right) Even though banks have more counterparties, the lower exposure to each separate one of them now makes them immune to a default by any single counterparty.
to drop to 10 at the same time as the first bank’s portfolio dropped to 8, then the
default of the first bank is enough to push the second bank into insolvency—this is pictured in
Figure 3. 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 because more than one of
the debts that they are owed are defaulted upon at once due to the correlation in other banks’
values.

Figure 5: With correlated portfolios, banks are now more susceptible to defaults of others, even when
levels of exposure to any single counterparty are low. This can undo the benefits of diversification and
the non-monotonicity discussed and now a second bank defaults even if it has ten partners.

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 co-defaults. 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 as 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 when the banks have
similar and under-diversified portfolios – for instance, all holding similar mortgages or loans –
as then they are correlated and risky.

3.2 Robust Yet Fragile

As stated by Haldane (2009), and studied in detail by Gai & Kapadia (2010), financial networks
have an intriguing property of being “robust-yet-fragile” Interdependencies between banks,
in the form of lending or liquidity provision 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

24For other examples and simulations of the impact of correlated portfolios on systemic risk, see the online
appendix of Elliott, Golub & Jackson (2014).
25See also Callaway et al. (2000) for an earlier discussion of percolation on graphs and such a tradeoff.
interdependencies can transmit the shock more widely and more extensively. There are, of course, nuances on this that depend on the model and the type of contracts that exist between institutions (e.g., see Allen & Gale (2000); Gai & Kapadia (2010); Gale & Kariv (2007); Elliott, Golub & Jackson (2014); Acemoglu, Ozdaglar & Tahbaz-Salehi (2015a)).

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

Acemoglu, Ozdaglar & Tahbaz-Salehi (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 those 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 its propagation. One can see a foreshadowing of this point in the analysis of Allen & Gale (2000) who show, 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, Gottardi & Vega-Redondo (2017) highlight the role of the size of shocks in a different model: one in which interdependencies between banks capture the correlation 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, they 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.

**Heterogeneous Network Structures.** Acemoglu, Ozdaglar & Tahbaz-Salehi (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 much interbank claims as liabilities, and all have the same number of counterparties. This rules out heterogeneity in bank size and in connectedness, as well as the possibility that a bank be a net lender or borrower.

Generally, analytic tractability limits full characterizations to such simple settings. An alternative is to use 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 in Elliott, Golub & Jackson (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, Haldane & Kapadia (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 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 (numbers of counterparties) can help make the network more resilient.

Given the complexity involved it makes sense to continue analyses in two directions: the development of more insights into how the structure of heterogeneity matters in financial contagion, and 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 simulation of risk patterns, an approach increasingly being used by regulatory institutions (Aikman et al. (2009); BCBS (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); Jackson & Pernoud (2020); D’Errico & Roukny (2019)), 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 reduces the risk of default cascades without impacting the values of banks. For example, Roukny et al. (2018) show that there exists 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 on
Both networks 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 on the right, there is a unique equilibrium in which all banks are solvent. In the network on the left there are two equilibria: one in which all banks are insolvent and default, and the other in which no banks default.

Figure 6: Both networks 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 on the right, there is a unique equilibrium in which all banks are solvent. In the network on the left there are two equilibria: one in which all banks are insolvent and default, and the other in which no banks default.

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

Gains associated with clearing cycles can provide some insight into the use of a risk manage-
ment 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 OTC trades through central counterparties (CCPs). CCPs allow
for multilateral netting of interbank contracts, which enhances transparency of the financial
network and limits counterparty risk. If interbank contracts are restricted to debt contracts,
such multilateral netting boils down to clearing cycles, as done in Figure 6.

4 Incentives in Financial Networks

Systemic risk depends on several factors – including network structure, the portfolios of institu-
tions 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 in-
centives; i.e., 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 potential for contagion they induce, 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 correlate their portfolios with that of their coun-
terparts. We discuss how the network structure comes into play in both of these inefficiencies.

**Inefficiently Risky Investments.** There are two main ways in which financial interdepen-
dencies 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 not only impact its 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 impacted
(Admati & Hellwig (2013)), with an early illustration of this being made by Jensen & Meckling

27 See [Duffie & Zhu (2011)] for more detailed discussion and background, and [Capponi & Cheng (2018); Wang; Capponi & Zhang (2020)] for more recent papers on the design of margin and collateral requirements for CCPs.
in which a manager makes choices that do not reflect shareholders’ interests. This has been investigated in a variety of network settings (Brusco & Castiglionesi (2007); Hirshleifer & Teoh (2009); Galeotti & Ghiglino (2019); Jackson & Pernoud (2019); Shu (2019)), where the externalities are very 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 has access to a safe asset with constant rate of return $1 + r$ and a risky asset with random return $\tilde{p}_i$, with $\mathbb{E}[\tilde{p}_i] > 1 + r$. Banks are furthermore linked to each other via financial contracts, that either take the form of 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 feedback 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, leading them to over-invest 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 (2017) consider a network of interbank liabilities, in which banks have the possibility of storing part of their initial cashflow 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.

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 (Bikhchandani, Hirshleifer & Welch (1992); Banerjee (1992); Chincarini (2012)), or the people who are choosing investments may worry about their reputations (Scharfstein & Stein (1990)). Other forces pushing towards correlation are regulations that limit the scope of investments, essentially pushing them to hold certain classes of assets, minimum amounts of certain assets, or to have a portfolio that meets certain risk characteristics. Banks also have forces that push them to the same lending strategies as their competitors (e.g., Cohen-Cole, Patacchini & Zenou (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 incentives 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 incen-
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 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 others’ 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, so are others, 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 derive from 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 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, Sanditov & Burger-Helmchen (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 impacted 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 highlight inefficiencies. Inefficient network formation is a recurring theme in the literature, starting with Jackson & Wolinsky (1996), but 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, some of which are based on the various roles of core banks as intermediaries in financial markets. Babus & Hu (2017) show that when partnerships between banks not only have 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 and 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. In Farboodi (2017), it is not information fric-
tions 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 over-connect whereas periphery banks under-connect – and the core captures intermediation rents. Finally, as Wang (2017) shows, a core-periphery structure can also stem from inventory efficiency. 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 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.

The potential inefficiency of a core-periphery structure usually comes from banks choosing either too few, or too many, counterparties given the externalities arising from, and the market imperfections that drive, intermediation. Beyond core-periphery structures, the number of counterparties a bank chooses can generate inefficiencies in itself, as it impacts 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 under-diversification 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 in Jackson & Pernoud (2019) shows that banks tend to choose too few counterparties on which to hold claims, because they overlook contagion costs others incur when they go bankrupt.

Furthermore, the equilibrium network exhibits ‘homophily’ in portfolios of outside assets (Elliott, Georg & Hazell (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 under-value diversification and prefer to be linked to those 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 push to 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 who can restructure their connections and sever outside ones. In their model, a bank defaults as soon as one of its counterparties does, so if any bank in a component defaults, then 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 their results can help explain

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28The incentives can also depend on the structure of the contract and bargaining between counterparties, as shown by Duffie & Wang (2016).
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, Ozdaglar, Siderius & Tahbaz-Salehi (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 involves a holistic view of the network. The following example illustrates 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 describes the amount of each type of financial assets and liabilities held by each bank. Depending on the jurisdiction, balance sheet data does not always provide complete, or even partial, information about one’s counterparties, and hence about the network structure. Such “local” data can completely miss which banks are most likely to start a default cascade, or be caught up in one. The point is straightforward, but worth emphasizing given its importance.

For ease of illustration, consider a network in which banks are only linked via debt contracts. A measure of systemic risk based on local balance sheet information only depends on the face value of each bank’s assets and liabilities, but not on the identities of its counterparties. To show why this is insufficient information, we give an example of 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 bailout one (and only one) of the two institutions, it could not make an optimal decision based on local information. Consider the network depicted in Figure 7.

Suppose the portfolios of Bank 1 and 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 $D$, Bank 3 below $D/4$, and Bank 5 above $D/2$. Let the recovery rate on assets of a defaulting bank be zero. Despite the fact that Banks 1 and 4 have the same balance sheet, only the former induces widespread default contagion if it remains insolvent. Indeed, Banks 2 and 3 have enough buffer to absorb

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29 Attempting to assess systemic risk without detailed network information is what [Jackson (2019)] refers to as “flying jets without instruments”: 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: Arrows point in the direction that a debt is owed. Banks 1 and 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.

the shock of Bank 4’s default, but not that of Bank 1. 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, even if one knows the portfolio realizations of 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.

While 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 only data from local stress tests, are at a substantial disadvantage.

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 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, Gorpe & Kok (2018); Farmer, Kleinnijenhuis, Nahai-Williamson & Wetzer (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 and 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 first.

**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 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 (Diamond & Rajan (2011); Bebchuk & Goldstein (2011)). If credible, this eliminates the possibility of miscoordination.

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 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), it 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 on the left of Figure 6. If someone were to inject 5 units of capital into either Bank 1 or 3, then there is a unique equilibrium in which all banks are solvent: 1 can pay 2 (even without any inflow from 4), which then can pay 3, etc. 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 Banks 2 or 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. They 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 miscoordination and self-fulfilling
crises is to have all transactions go through a Central Clearing Counterparty (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 be socially costly in that sense — we discuss the interplay between regulation and incentives in Section 5.3.

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, constraining the types of investments that different institutions can make, and monitoring banks’ capital ratios and investments on an ad hoc basis. A second is to allow arbitrary investments but then intervene and inject capital if some danger of cascading defaults 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. 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.

The determination of which financial institutions contribute the most to systemic risk, can be measured via 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 it itself contributes to it. Some of these measures are solely based on market data on portfolio returns of individual banks, and include features of contagion either through fire sales (Duarte & Eisenbach (2018); Engle & Ruan (2019)) or the correlation structure of returns between

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30 See Martinezy et al. (2020) for a discussion of 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.

31 See also Belhaj et al. (2020) for more discussion of centrality and prudential regulation.

32 See Lucas (2019) for an estimate of bailout costs in the 2008 financial crisis.

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

34 Paying attention to centrality makes more of a difference in asymmetric networks, such as core-periphery ones, compared to more regular networks (e.g., see Capponi & Chen (2015)).
bank portfolios (Billio et al. (2012)). Others are based on the underlying network of interbank contracts and rely on models of contagion via counterparty risk (Amini et al. (2016); Hauton & 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. It 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, etc. 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 just the payment streams.

Public bailouts come at a cost to the regulator, and in particular 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 portfolio, 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, Corell & Stiglitz (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 structure 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, Carvalho, Ozdaglar & Tahbaz-Salehi (2012); Barrot & Sauvagnat (2016); Ramirez (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 incentives of market participants is only partly understood. Accounting for responses to regulation can change some comparative statics and policy implications.
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 then no longer suffer the costs of risky investments. The mechanism through which this works is nuanced, since the shareholders who control a bank may not gain value during a bailout, whereas debt-holders would. But there are a variety of reasons why the management of a bank may wish to avoid insolvency, that have nothing to do with equity value. There is evidence that this matters as, 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 U.S. in the early 19th 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 not only affect banks’ investment decisions, but also their choice of counterparty, 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 U.S. 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.

Public Bailouts, Private Bail-Ins, and Counterparty Choice. Given the high financial cost of public bailouts and the perverse incentives that they generate, attention has been paid to private-sector resolutions of defaults, especially since the last financial crisis. Private-sector bail-ins – 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

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35This can even happen with private bailouts, as shown by Elliott, Golub & Jackson (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.
costs induce private-sector bailouts, as they magnify losses due to defaults.\footnote{In settings without any bankruptcy costs, incentives can completely disappear, as shown by \cite{Rogers2013}.} He examines the incentives of coalitions acting together to avoid defaults, and shows that non-clustered networks with intermediate levels of interdependencies lead to optimal incentives. Furthermore, if the network is clustered, then 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, \cite{Bernard2017} 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 system. Hence, the more diversified a network is, the less individual banks are willing to step-in and rescue each other.

**Shadow Banking and Moving Targets.** One important and problematic characteristic of financial networks is their complexity, which can make them opaque.\footnote{In addition, the financial organizations involved may be concerned about keeping information about their trading positions and partners private. See \cite{Hastings2020} for a discussion of some related issues, and new methods of obtaining critical network information while preserving privacy.} 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 (\cite{Silber1983}).\footnote{See \cite{Anderson2020} for an analysis showing how growth in shadow banking interacts with interventions within the banking sector, and can exacerbate risk.} Importantly, a significant portion of these trades are realized in over-the-counter markets, and are hence may only known 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 costs of improving transparency, which is a new direction explored by \cite{Ramirez2019}.

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, making 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, it 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 capital to the shadow banking system.
Once those were regulated, one could see new forms of unregulated institutions emerge, 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 considered as 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 then be regulated in a similar way?

5.4 Political Challenges

As should be clear from our discussion above, regulation is far from one-size-fits-all, and optimal intervention depends on many factors, including network positions and centralities that are constantly shifting. Unfortunately, regulations are slow to adjust and often constrained by politics, since intervention can benefit some parties more than others. Historically, regulation has surged after financial crises (e.g., the Glass Steagall Act and Dodd-Frank) and then slowly eroded over time until another crisis hit. 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 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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6 Some Background on Financial Interconnectedness

Before getting into the review of the literature on systemic risk and financial networks, it is useful to provide some empirical background and context, which is the purpose of this section. Anyone who reads Janet Yellen’s (2013) speech, or the book by Reinhart & Rogoff (2009), will realize that systemic risk is not a new phenomenon. Nonetheless, the extent of the network across borders has increased, and this means that a crisis in one country can quickly become an international crisis; and the 2008 financial crisis illustrated the global nature of our financial network quite clearly. In addition, the size and centrality of some of the largest players is reaching an unprecedented scale, and at the same time the network is becoming more complex and harder to track, as it involves more diversity and specialization than ever. We detail these facts below. We also mention two other important background facts that are less about how the financial system has evolved, but instead provide new information about potential dangers and costs in the system. The first concerns the high correlation in portfolios that linked financial institutions hold – which leads to increased dangers of cascades due to correlated times at which financial institutions are vulnerable; and the second concerns the size of bankruptcy costs – which are one important part of the economic damage that cascades in a financial crisis.

6.1 Globalization and Financial Interdependencies

World trade grew from just under 20 percent of world GDP at the end of the Second World War to over 60 percent by 2015. It is not a coincidence that the world poverty rate fell from over 40 percent in the early 1980s to below 10 percent in 2020. This trend was matched by a tenfold decrease in the incidence of wars, by multiple measures: effectively, trading partners almost never go to war with each other. These enormous benefits mean that there are strong reasons that we should welcome the very large network that has emerged. Nonetheless, such growth in interconnectedness comes with risks of systemic disruptions - both via the increasingly complex supply chains and the financial networks that support the whole system.

Indeed, the accompanying growth in cross border finances is impressive. For example, 17 percent of equities and 18 percent of bonds around the world were held by foreigners in 2000, and that rose to 27 percent of equities and 31 percent of bonds by 2016. This matches up with the investments (debt, equity, FDI, lend/other) around the world that come from foreign sources; which at the more than 132 trillion dollars in 2016 (Lund & Härlé (2017)) – compared

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40 Imports plus exports over GDP. Detailed data can be found for 1870-1949: Klasing & Milionis (2014); 1950-1959: Penn World Trade Tables Version 8.1; 1960-2015: World Bank World Development Indicators.

41 World Bank Poverty Report.

42 See Jackson & Nei (2015) for more empirical background and analysis of the relationship between increased trade and decreased interstate armed conflict.
to a total level of world investments of just over 300 trillion dollars – is well more than a third of all finances.

6.2 Consolidation

The financial/banking sector has grown enormously, but has also consolidated, with far fewer banks and those being much larger than they used to be. In 1980 there were 14 thousand commercial banks in the US according to the FDIC\textsuperscript{43} with total assets of 2 trillion dollars. In 2018 there were 4.7K with 16.5 trillion dollars in assets. So the number of banks has dropped to a third of what it was, and at the same time banks are managing more than eight times as much in terms of total assets\textsuperscript{44}. This consolidation has continued to grow even after the 2008 financial crisis. For example, in 1990 the five largest banks in the US held 10 percent of total financial assets, in 2007 they held 35 percent, and in 2015 45 percent. The ten largest banks in the world controlled 26 trillion dollars in 2016. To put that in perspective, the US and Chinese combined GDP in 2016 was 29 trillion dollars, and the world GDP was 75 trillion dollars.

6.3 The Spectrum and Role of Financial Intermediaries

It may seem paradoxical that the growth in the size of the banking sector and consolidation in the number of banks have been accompanied by a proliferation in the number of different types of financial intermediaries and increasing specialization in their roles\textsuperscript{45}. To fix ideas consider the following illustration. A century ago a mortgage was typically issued by a bank and often it was the sole intermediary between that borrower and the bank’s depositors who were the effective lenders. The bank served a number of roles. On one end, it took in deposits from people who had different and random times at which they needed their money back, and valued some flexibility in their ability to withdraw funding. By pooling the money from many different depositors and taking advantage of laws of large numbers, it could largely predict when it would need to pay parts of the funding back to its depositors, and hence had reliable streams that it could lend out for fixed durations\textsuperscript{46}. This allowed it to lend money out in a portfolio of mortgages of different maturities and risks. On this other end, the bank helped the borrower select an appropriate mortgage, and screened the borrower to ensure that he had good credit and that the property and situation was properly evaluated in terms of the risks involved. It also monitored the loan and collected the payments over time. There were significant economies of scale not only in pooling the deposits, but also in having an intermediary with the expertise of evaluating prospective borrowers, marketing the mortgages, collecting payments, and balancing the portfolio to match with the depositors’ needs.

\textsuperscript{43}See https://www5.fdic.gov/hsob/HSOBFullRpt.asp
\textsuperscript{44}Part of this change is due to changes in regulations, such as undoing the separation of investment, commercial banking, and insurance, that had been required under Glass Steagall. However, this trend is also seen outside of the US, reflecting large economies of scope and scale in the banking sector.
\textsuperscript{45}A general role of intermediaries arises from providing liquidity in markets where there can be temporary imbalances between buyers and sellers, or where centralized trade can lower search costs. For some background, see Demsetz (1968); Gehrig (1993); Spulber (1996); O’hara (1997); Brusco & Jackson (1999).
\textsuperscript{46}For basic models of this, see for instance, Diamond & Dybvig (1983); Allen & Gale (2000).
Over time the chains of parties involved in this financial intermediation has grown as the multiple roles of the bank have been separated. A mortgage may now be issued through a broker who provides the sales and marketing expertise. The brokers work with a multitude of firms who do the actual issuing of the mortgages, including banks as well as other companies. They specialize in documenting the circumstances of the borrower and property involved and then often resell the mortgages. Many mortgages are purchased and held en masse by entities that collect the payments and then resell those streams of payments in different tranches (packages of mortgages grouped by risks and maturities) in the form of mortgage-backed securities. Those securities might be bought by banks and other investment companies who then package them together in portfolios either to pay interest to their depositors or offer them as part of investment funds to private investors. Along the way, various parties in this chain insure and hedge their risks via a variety of derivatives and insurance contracts that are often sold by other firms that are separate from all the others in the chains.

In this example, the many roles that were filled historically by a single bank have been separated: the broker provides sales expertise, the mortgage company does due diligence on the borrower and property, the next buyer and repackager of the mortgages pools risks and takes advantage of economies of scale to eliminate idiosyncratic risks and provide a more predictable return on a security, the purchasers of those securities provide returns and flexibility to large numbers of depositors who want random access to their funds as well as some return on their investment. In some cases, several of these services are provided by different parts of a single bank holding company, but some are no longer part of the banking sector and have become part of a shadow banking sector.

This is just one example, and there are many other situations that involve multiple intermediaries including insurance, venture capital, corporate lending, and many other forms of investments. In sum, there has been a proliferation of different types of financial intermediaries who specialize in different parts of the chain between the ultimate borrowers and lenders; at the same time as the substantial economies of scale in many of the particular roles have led to consolidation and concentration within each role.

This proliferation leads to a challenge in evaluating systemic risk: the networks involve organizations that fall into different regulatory jurisdictions, and some important players are not actively monitored at all.

\footnote{As we saw in the 2008 financial crisis, there can be failures to properly fulfill their roles by all parts of these chains (e.g., see the discussion in Chapter 4 of \cite{Jackson2019}). There were brokers paid by commission per loan encouraging buyers to take on loans that were inappropriate for them. Some of the largest firms issuing mortgages did not screen the loans properly and were fraudulent in what they told buyers about what they resold (e.g., Countrywide Mortgage). Many mortgages were sold to large mortgage warehouses such as Fannie Mae and Freddie Mac (FNMA and FHLMC) who ended up improperly valuing the trillions of dollars worth of mortgages that they were buying. A variety of asset-backed and mortgage-backed securities were being insured by AIG, which ended up not even having the capital to make margin payments on some of the contracts it sold. The securities were bought in large amounts by various banks and investment banks who over-valued them (e.g., Bears Stearns and Lehman Brothers), leading to excess risk and eventual defaults to their investors and depositors.}

\footnote{See \cite{GlodeOpp2016}; \cite{GlodeOppZhang2019} for models of OTC markets with asymmetric information, in which longer intermediation chains can sometimes improve trade efficiency.}
6.4 Core-Periphery Structures

One microcosm of the different roles of financial intermediaries discussed above is reflected in the structure of the banking sector itself, which is often crudely divided into two parts: a core of very large national/international banks and a periphery of smaller (but often still large) regional banks. The core banks are highly interconnected with each other, whereas the rest of the network is usually sparse, with regional banks each only interacting with a few of the core banks. Empirical studies of financial networks, and especially interbank lending, have highlighted this core-periphery structure. For instance, Soramäki, Bech, Arnold, Glass & Beyeler (2007) detail a completely connected core of 25 banks, including all of the largest ones, that borrow from and lend to each other; with large exposures between them. Other studies of such structures include Bech & Atalay (2010) for the US, Upper & Worms (2004) and Craig & Von Peter (2014) for Germany, and Blasques, Bräuning & Van Lelyveld (2018) for the Netherlands. As alluded to above, there are a variety of reasons to expect a core-periphery structure as there are advantages to having a concentration in the core of intermediaries, which can then use large economies of scale to better manage their inventory and match buyers with sellers (e.g., see Craig & Von Peter (2014); Babus & Hu (2017); Farboodi (2017); Wang (2017)), while the periphery can specialize in local expertise in making loans.

In terms of understanding systemic risk, the dense connections within a core-periphery structure also have contagion consequences. For instance, Elliott, Golub & Jackson (2014) show how the core can lead to much more extensive default cascades for wider ranges of transactions than more balanced networks. This is exacerbated by the fact that core organizations often have very similar businesses and thus very correlated investments, which leads them to be vulnerable at the same time, as we discuss next.

6.5 Correlated Investments

The financial crisis of 2008 was an obvious situation in which many financial institutions were heavily exposed to the same mortgage and subprime mortgage markets, and had extensive exposures to each other at the same time. Since then, several studies have examined this sort of correlation explicitly, and it continues. For instance, Elliott, Georg & Hazell (2018) find that German banks are more likely to lend to banks with portfolios similar to their own: going from the 25th to 75th percentile of similarity in portfolios between two banks increases their lending to each other by 31 percent. They also find an effect on the extensive margin in terms of the probability that they lend to each other at all.

This sort of correlation occurs for many reasons. Four primary ones are as follows.

First, competition between institutions can lead them to choose similar investments. This was something that contributed to the savings and loan institutions’ extensive exposure to fixed-
rate mortgages and later to junk-bonds and the S&L crisis of the 1980s and 90s. This happened since savings and loans that took riskier positions could offer higher interest rates on their checking and savings accounts (and given that much of their pre-existing fixed-rate mortgage portfolios were paying below-market returns, they had to find very high return investments to match the high market interest rates that were prevalent at the time). Since many of these were insured accounts, depositors had incentives to shop for the highest interest rates. This means that in order to attract and keep depositors, savings and loans had to compete to offer the highest interest rates. Since the place they could earn the higher expected rates of return that would enable them to offer higher interest rates was in riskier investments, and in the junk-bond market in particular, this drove them to take increasingly risky positions. This incentive is not unique to the savings and loan crisis, but is more commonly at work in the banking sector.

Second, there can be regulations restricting the sorts of investments that banks and other financial institutions can make with some of their capital, or other requirements on which sorts of assets they can use to satisfy reserve requirements or can use for short term lending and repos. If banks need to hold some percentage of their portfolio in bonds issued by some countries (e.g., European countries) then it is not surprising that they all have nontrivial amounts of investment in bonds that offer higher returns (e.g., Greek debt in 2010, just before their debt crisis). This can correlate their portfolios and make them susceptible to the same shocks.

Third, as we discuss more extensively below, banks have very strong incentives to deliberately choose portfolios that are correlated with those of their counterparties. This follows since they benefit most from being solvent when they earn the greatest returns from their counterparties and insolvent when their counterparties are insolvent.

Fourth, regardless of the short-run correlations in bank portfolios, there can also be large economy-wide shocks, such as the lost production and employment due to covid-19, which affect the portfolios of almost all financial institutions in the same direction at the same time.

6.6 Bankruptcy Costs

The externalities between financial organizations matter not only because of the basic investment distortions that result, but also because of the substantial frictions and costs of bankruptcy that are present in financial networks. If a large counterparty of some financial organization defaults, that can result in large losses for the organization, and ultimately cause it to default as well.

These costs are of fundamental importance, since otherwise defaults or changes in values in the financial system only determine which organizations have which values, but not the overall total of those values. Bankruptcy costs due to insolvency are important in leading to extra drops in values, cascades of those losses, and overall depression of values.

As an example of the scale of real economic costs when there are defaults, let us have a look at the Lehman Brothers default. In that bankruptcy there were initially 1.2 trillion dollars of claims made against Lehman Brothers. Of these, the courts ultimately allowed only 362 billion

52This can interact with miscategorization by ratings agencies. If ratings agencies mistakenly list some assets as being of a higher class than they should be, then that may qualify those assets to be used for “risk-free” purposes, even though they are risky and are thus offering higher expected returns.
dollars of claims, and then those creditors only received 28 percent of that reduced number. This was an extreme case, but there are substantial frictions, delays, and inefficiencies that result from bankruptcy, especially in troubled times. These result from fire sales, early termination of contracts, the complexity of contracts that need to be unwound, lengthy negotiations, legal costs, among others. Estimates of bankruptcy recovery rates are in the 56-57 percent range – so that more than 40 percent of the value of an organization going into bankruptcy is lost in the process. Of the amounts that are lost about 4/11 is attributable to legal costs and the other 7/11 to a drop in asset value (some from liquidation). Moreover, recovery rates are another 15 to 22 percent lower in distressed times which would typically apply during a large financial crisis.

53 See Fleming & Sarkar (2014).
54 See Branch (2002); Acharya, Bharath & Srinivasan (2007), as well as Davydenko, Strebulaev & Zhao (2012); James (1991).
55 See Acharya, Bharath & Srinivasan (2007); Bruche & Gonzalez-Aguado (2010).
7 An Executive Summary

• Financial intermediation is vital to any economy:
  – It takes advantage of economies of scope and scale in pooling idiosyncracies on both
    borrowing and lending sides, provides trading opportunities when long and short
    sides are unbalanced, provides screening and monitoring of investments, and matches
    funds to investments.
  – However, it also involves substantial externalities as financial intermediaries are in-
    terconnected and interact through substantially incomplete markets, and face sub-
    stantial bankruptcy costs and inefficiencies due to lost investments during crises;
    which cause real damage to the economy, especially when they cascade.
  – We discuss the various ways financial interconnections generate systemic risk, the
    inefficiencies that ensue, as well as when and how oversight, regulation, and inter-
    ventions are useful.

• Financial intermediaries and other financial institutions are interconnected in several
  ways:
  – via a variety of explicit contracts that directly expose them to each other;
  – via similar investments and correlation in the values of their portfolios; making them
    vulnerable to the same forces at the same time;
  – via investors’ inferences about the health of one institution from the values of others.

• Correspondingly, systemic risk comes from several forms of contagion:
  – via cascading defaults and costs of insolvencies, which are exacerbated by contem-
    poraneous weaknesses due to correlated portfolios;
  – via fire sales which depress values of commonly held assets;
  – via uncertainty, fear, and inferences that can result in runs by depositors and in-
    vestors, as well as credit freezes in the network itself;
  – via multiple equilibrium values due to coordination in payments.
  – In some crises, all of these interact at once, as a bank can be vulnerable for one
    reason (e.g., due to a liquidity shortfall and credit freeze, or run, or losses due to
    depressed asset values due to another bank’s fire sale) and can then cause a cascade
    for another (e.g., default on its liabilities).

• Network structure is essential to understanding contagion and systemic risk:
  – financial networks are “robust-yet-fragile”: interconnections help in diversifying some
    risks and avoiding individual defaults as banks can insure each other against liquidity
    shortfalls, but the interconnectedness makes the network more susceptible to larger
    losses in fundamental asset values that then cascade;
there is a non-montonicity in how interconnectedness affects contagion: without any connections there can be no contagion, with intermediate levels of connections an institution is heavily exposed to each of its counterparty’s default and the whole system is at risk, while when institutions have many counterparties then no individual default is contagious and contagion becomes less likely;

- correlation in portfolios can greatly increase the probability of systemic failure and can undo the benefits of having many counterparties;

- the risk of contagion depends on the distribution of exposures across banks and the specific structure of the network (e.g., core-periphery networks act differently than other more balanced networks, being more susceptible to some shocks and less to others);

- whenever defaults involve some deadweight costs, cycles in the network (of debt, equity, and other contracts) can generate multiple equilibria and enable self-fulfilling cascades of defaults;

- the types of contracts connecting firms (debt, equity, derivatives) matter, and equity-like contracts can lead to fewer defaults than debt-like contracts all else held equal.

• Financial institutions’ investment decisions have externalities that they do not internalize. They have incentives:

- to take on more risk than is socially optimal since they see the returns, but do not experience the full costs of defaults, bankruptcies and other cascading effects;

- to take on too few counterparties and do too much business with each, inducing excess systemic risk;

- to correlate risks with their counterparties so that they are solvent when their counterparties pay off on contracts, but are insolvent when their counterparties default;

- and to connect with those others with whom they are most correlated.

- Reputations and costs of capital can counter some of these incentives, but generally do not fully eliminate these moral hazard problems.

- In some circumstances, banks have incentives to bail each other out rather than face losses due to another’s bankruptcy costs, which can avoid a crisis.

• Different forms of regulation, oversight, and intervention can address different aspects of systemic risk:

- Explicit/implicit insurance of contracts and payments can eliminate fears, runs, contagion by inference, and credit freezes.

- Networks are needed to understand and evaluate risks and to identify optimal ways to intervene, including via bailouts, regulation, and injection of capital:
  * Stress testing should be network-based, and correlations in portfolios mean that rare events may not be so rare.
Understanding externalities and excess correlation and risk taking requires network information.

Potential multiplicity of equilibria requires identifying cycles.

When multiple equilibria are present due to cycles, bad equilibria can be eliminated by:

- ‘compression’ (the canceling out of cycles);
- the guarantee of payments;
- restructuring the network (e.g., via CCPs), but such ‘star networks’ are vulnerable to failure of the CCPs;
- minimal injections of capital, the amounts of which and points of injection can be fully characterized as a function of cycles in the network.

Default cascades can be avoided before they start, or halted after they start by combinations of restrictions on investments (e.g. reserve requirements, capital ratios, restrictions on correlations of assets with counterparties) and bailing out insolvent institutions by making (some of) their payments.

Whether it is better to restrict investments, insure with ex post bail outs, or not intervene at all, depends on the financial centrality of the institutions in question, the network structure, and cost of bailout capital.

The relevant measure of ‘financial centrality’ depends on the specific circumstances and network in question:

- institutions can be central without being enormous;
- contracts beyond debt matter and cascades can happen without explicit defaults by all involved (e.g., a drop in the equity value of one institution can push another holding that equity into insolvency);
- correlated investments matter;
- centrality can be defined directly via the network;
- different networks interact and a firm might be vulnerable in one network (e.g., via runs and inference from some other failure) and then cause a cascade into another (e.g., then default on its payments), and so full evaluation requires mapping multiple networks.

The financial system is dynamic and reacts to regulation:

- some investors shift funds to institutions that are less constrained (regulated) and can offer higher returns;
- new institutions grow outside of regulatory boundaries, and the shadow banking system is large and difficult to observe;
- investments cross international jurisdictions, making it hard for any regulator to view the network;
- financial networks are intertwined with international supply chains that have grown increasingly large and complex.