Bank capital shock propagation via syndicated interconnectedness[*]

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Abstract

We study how shocks to bank capital transmit through the syndicated loan market, the main source of bank funding for large corporations. We capture key features of the syndicated loan market in a micro-founded model, which allows a bottom-up analysis of the market's resilience to shocks. Model simulations, calibrated to empirical data, indicate that shocks to bank capital can produce rare events in the market when the use of a common risk management tool such as Value-at-Risk (VaR) is combined with shared loan exposures. The emergence of a long tail in the distribution of dissolved loans is robust to alternative shock specifications and network topologies, suggesting a presence of amplification effects. At the same time, the empirical network degree distribution also points at the core-periphery structure, which is somewhat localized, so might subdue systemic events. In addition, when bank capital ratios are raised to meet tighter VaR constraints, the greater threat of violating the VaR constraint due to an equity shock is largely offset by the banks' preventive measure to unload risks beforehand.

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I. Introduction

The erosion of bank capital and the subsequent deleveraging cycle in the aftermath of the 2008 Lehmann collapse served to transmit credit crunch to the real economy. Such episodes underline need to better understand the mechanisms behind the propagation of bank distress to the broader economy. This paper examines the propagation of bank capital shocks in one important segment of international credit markets: the syndicated loan market.

Over the last 30 years, the syndicated loan market has evolved into the main vehicle through which banks lend to large corporations (Ivashina and Scharfstein, 2010a). In 2007, international syndicated loans made up 40% of all cross-border funding to firms in the United States and more than two thirds of cross-border flows to emerging markets (De Haas and Van Horen, 2012). Syndicated loan interlinkages among banks have also been shown to have positive impact on trade, foreign direct investment (FDI), and cross-border portfolio flows through various direct and indirect channels (Hale, Candelaria, Caballero, and Borisov, 2011, 2013). At the same time, the market is characterized by the sensitivity to banks' balance sheet constraints and rapid adjustments. Recent empirical literature suggests that the withdrawal of banks from syndicated lending in 2008 was particularly swift and this may have contributed to the rapid spillover of the subprime shock across borders.[1] Yet, despite its central role in international financial intermediation, the financial stability implications of the structure of the syndicated loan market have been little explored.

In this paper we build a micro-founded model of syndicated lending and study the systemic implications of the market's structure when banks face shocks to their capital. As in Danielsson, Shin, and Zigrand (2012) and Adrian and Shin (2014), banks operate subject to a value-at-risk (VaR) constraint. This seems an obvious choice to model bank behavior, since regulators impose capital requirement on financial institutions to mitigate insolvency risk. For instance, the Basel Committee on Banking Supervision imposes capital requirements that depend on VaR estimations. Hence, when banks face an erosion of their equity capital, the first order of adjustment is likely to be on the asset side, for example by shedding "non-core" business activities or reducing

[1] For instance, as the market collapsed during the first year of the global financial crisis from approximately 800 to 300 billion US dollars in quarterly issuance volume (Gadanecz, 2011), international trade experienced the most sudden, severe, and globally synchronized collapse on record (Antonakakis, 2012). On the sensititivy of syndicated loan market to banks' balance sheets and its rapid speed of adjustment see Chui, Domanski, Kugler, and Shek (2010), Ivashina and Scharfstein (2010a), and De Haas and Van Horen (2012).

riskier lending.

We first show that a market for syndicated loans emerges naturally after allowing syndication in a model with risk-neutral banks who optimize their loan portfolios under a VaR constraint. We then calibrate the model parameters to reflect key syndicated loan and bank characteristics and simulate the propagation of bank equity shocks under alternative shock distributions and network topologies. By basing the model simulations on behavioral microfoundations of optimizing agents, we are aiming to address the critique of Upper (2011), who points out that in order to reproduce non-linearity and threshold effects that lead to rare systemic events, it is necessary to look at strategic complementarities in bank behavior in addition to direct on-balance sheet linkages.

Our findings are five. First, we find that a common equity shock is the most evident driver of rare events in this market (defined as an aggregate rate of dissolved loans in excess of 30%). While in the absence of a common component to bank equity shocks the market is quite stable, when a common component is introduced the distributions of withdrawals from lending and of dissolved loans shows a long tail.

Second, we show that syndicated interconnectedness matters for the propagation of bank distress in the system. With loan syndication there are incidents of massive dissolution of loans even when the negative common shock is mild; whereas it takes a large negative common shock to cause substantial dissolution of loans when banks are independent. This suggests that the market structure specific to the syndication process serves to propagate bank equity shocks, amplifying market disruptions in periods of stress. Importantly, these dynamics occur in a rational equilibrium setting, whereby banks know the true distribution of shocks yet still behave in a way that generates tail effects in aggregate lending that are not warranted by the distribution of exogenous shocks themselves.[2]

Third, the aggregate effects of a common equity shock are present across different network shapes. These are homogeneous-degree network, network with uniformly distributed degrees, and the empirical networks based on Euclidean distance in banks' loan portfolios or based on the direct links to lead arrangers. Among different network structures we find that the homogeneous-degree network is least stable. The equilibrium distribution of withdrawals and syndicate dissolutions in

[2]This differs from the results of Caballero and Simsek (2013), who study the propagation of liquidity shocks through interbank markets with the uncertainty about the network itself (e.g., Knightian uncertainty) serving a key driver.

the homogeneous-degree network exhibits a form of bifurcation, whereby the aggregate outcome in response to the same size common equity shock can be in one of two extremes: zero loan dissolutions or more than 50% dissolved. This points at a form of efficiency-stability trade-off characteristic of fragile market structures, should the actual empirical network approach this homogeneous case.

Fourth, the actual empirical network points at a more stable core-periphery structure. The simulation of aggregate withdrawals suggests that this actual loan network is more localized than the homogenous-degree network, which might subdue systemic events.

Lastly, we conduct two simple policy experiments. In one, we hit a bank which has the highest number of syndicate participations with a large unexpected negative equity shock. The resulting simulations show only a moderate increase in the probability of large withdrawals and syndicate dissolutions. This suggests that the failure of a highly interconnected bank may not necessarily generate a large systemic event in this market as it is organized currently. In another experiment, we tighten the VaR constraint to mimic an environment of higher capital ratios. Simulation results suggest that the greater threat of violating the VaR constraint due to an equity shock is largely offset by the banks' preventive measure to take on less risk portfolios.

The model further reproduces three stylized facts identified by the existing literature and present in the data from the crisis period.[3] First, the market is subject to very rapid adjustments in times of stress (the total volume of syndicated loans reported in Dealogic contracted by approximately 43% in 2008). Second, most of the adjustment takes place along the extensive rather than the intensive margin. Specifically, from 2007 through 2009, about 4/5 of the contraction came from the reduction in the number of loans, and only 1/5 from the average loan size. The total number of unique tranches declined from 15,070 to 11,556, while average tranche size declined only by 13%, from \$305 to \$266 million. Third, the immediate contraction in lending comes from banks not responsible for originating the loan (see Figure 1, left-hand panel); at the same time, the average loan share of lead arrangers actually increased from 28 to 30% during the crisis (see Figure 1, right-hand panel). This indicates that, to the extent possible, lead arrangers had been compensating for the withdrawals by other syndicate participants.[4]

[3] We rely on Dealogic Loan Analytics database to draw out stylized facts about syndicated loan market dynamics and for parameter calibration.

[4] These numbers are comparable to Allen and Gottesman (2006) who show that the loan share held by lead arrangers has on average been 27%, compared to the average loan share of 3% held by syndicate participants.

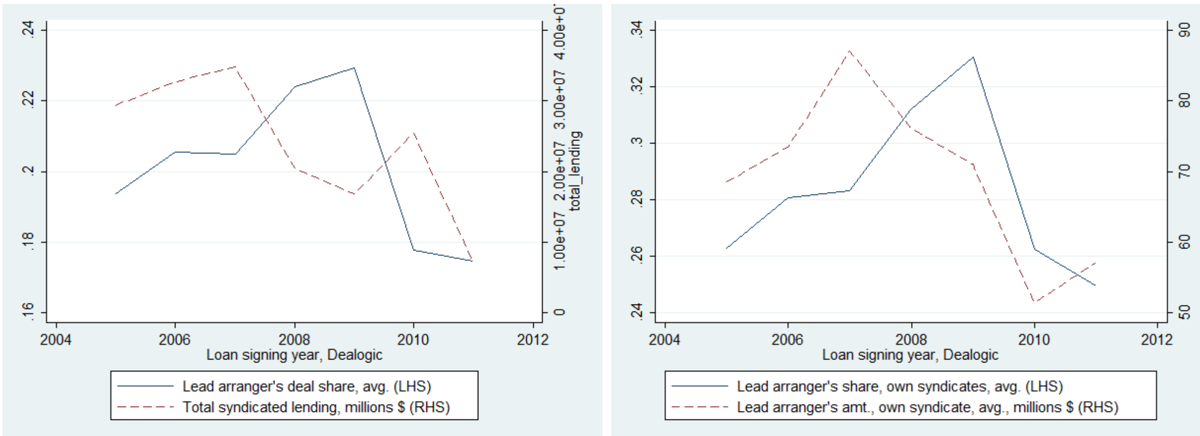


Figure 1. *Left:* inverse relation of lead arrangers' share of total lending; *Right:* asymmetric exposure of lead arrangers

This paper is related to two strands of literature. One strand is the literature on risk management by financial intermediaries and the role of bank capital constraints in the propagation of shocks. Adrian and Shin (2010) have shown that when banks target the level of equity capital to satisfy the VaR constraint, this introduces procyclicality in their balance sheet management and can feed into aggregate asset price fluctuations.[5] Danielsson, Shin, and Zigrand (2012) derive a closed form solution to the dynamic problem of balance sheet management by capital constrained banks, while Adrian and Shin (2014) go one step further to provide possible microfoundations for the widespread use of VaR.[6] Other papers examine the consequences of balance sheet constraints for the international propagation of shocks. In a general equilibrium open economy model, Pavlova and Rigobon (2008) demonstrate how portfolio constraints lead to cross-country spillovers of financial shocks and increase asset price correlations. Devereux and Yetman (2010) model two countries populated by savers and investors to show that a combination of leverage constraints with overlapping portfolio holdings produces a powerful cross-country financial transmission channel. These findings have been challenged somewhat by van Wincoop (2013), who also uses a two-country model with leveraged financial institutions, but finds that it cannot reproduce the magnitudes in transmission and asset price fluctuations observed in the data.

[5]This approach contrasts with He and Krishnamurthy (2013), for example, who use log utility with risk averse agents and derive a feature that leverage is countercyclical.

[6]More generally, robust empirical relationship between bank capital and lending, as well as the ability of equity capital to serve as a buffer against negative shocks, is found by Gambacorta and Mistrulli (2004), Berrospide and Edge (2010), Cornett, McNutt, Strahan, and Tehranian (2011), Gambacorta and Marques-Ibanez (2011), and Carlson, Shan, and Warusawitharana (2013).

The second strand is the literature on syndicated lending networks. Networks are endogenous to the process of syndication as banks become more strongly connected to one another as a result of collectively lending to the same borrowers. Hale (2012) uses data on bank relationships through syndicated lending to each other to find that global banking network responds to economic and financial shocks. Cai, Saunders, and Steffen (2011) find that closer syndicates have safer borrowers and safer loans but more interconnected lenders contribute more to systemic risk. Bos, Contreras, and Kleimeier (2013) show that over the past 20 years the global syndicated network for corporate loans has become more interconnected with lead arrangers becoming increasingly active, hence increasing the network density. There is also evidence that countries in which banks were more connected to other banks through syndicated loan market experienced a lesser impact of the global financial crisis (Caballero, Candelaria, and Hale, 2009).[7] While the most centrally located banks (which tend to be large and reputable global institutions) appear safer on average, Hale, Kapan, and Minoiu (2013) show that those banks that intermediate between the central and peripheral ones appear more exposed and exhibit significant losses during crisis times.[8]

By merging the two strands of literature, our paper is the first to introduce explicit bank optimization behavior in the context of syndicated loan networks. This allows for a more structural approach when studying the resiliency of this market. Such bottom-up analysis can also help identify market features and conditions that make the contagion from bank capital shocks more likely.

The remainder of the paper is organized as follows. Section II presents the model. Section III shows simulation results under alternative network topologies and shock distributions. Section IV concludes.

[7] In terms of geographic proximity, De Haas and Van Horen (2012) use more traditional empirical tools to find that banks continued to lend more to countries geographically close, where they are integrated into a network of domestic co-lenders, and where they have more lending experience. Such bank-borrower closeness may matter especially in times when a firm"s net worth drops (Ruckes, 2004) or for carving out local captive markets (Agarwal, 2010).

[8] At the more aggregate, banking system or country level, the network analysis of cross-border banking can also be done using the BIS banking statistics: Hattori and Suda (2007) and Minoiu and Reyes (2013) examine international banking networks using BIS consolidated and locational banking statistics respectively.

II. Model

This section develops a micro-founded model of syndicated lending.[9] The basic setup resembles Danielsson, Shin, and Zigrand (2012) and Adrian and Shin (2014), whereby risk neutral banks maximize returns subject to a value-at-risk (VaR) constraint. The model is augmented with the formation of syndicates, allowing banks to trade a share of a loan to benefit from risk-sharing. Reflecting the specificity of the market, each project is financed by a lead arranger, who in effect underwrites the loan. Lead arrangers follow a threshold rule, whereby dissolving the syndicate in response to a sufficiently adverse own equity shock or in response to participant withdrawals.

A. *Autarky – No risk sharing*

We begin by defining a benchmark without loan syndication (autarky). There are N investment projects of equal size, $X_1, \ldots, X_N$. For simplicity, we assume equal characteristics for all investment projects, so that the return to project j, R'_j, is normally distributed with mean R and variance σ^2 and independent across projects. We further assume that banks can only invest into one project.

The bank's investment is subject to a Value-at-Risk (VaR) constraint: $\Pr(R'_j X_j < -e) \leq \alpha$, where e is the bank's equity (common across banks) and α is the tolerance level for insolvency probability. Since R'_j follows a normal distribution, the VaR constraint can be rewritten as $\Phi((-e - R'_j X_j)/(\sigma X_j)) \leq \alpha$, where Φ denotes the standard normal distribution function. Define ϕ such that $\Phi(-\phi) = \alpha$. Then the VaR constraint is expressed as

$$\frac{e + E(R'_j X_j)}{\sqrt{V(R'_j X_j)}} \geq \phi. \tag{1}$$

[9] The syndicated loan market follows an "originate-to-distribute model," whereby the originating bank, dubbed lead arranger or lead manager, retains about a third of each syndicate loan on average (Allen and Gottesman, 2006; Ivashina and Scharfstein, 2010b). The remaining share is sold to a syndicate of investors including banks, pension funds, mutual funds, hedge funds, and sponsors of structured products. The lead arranger(s) screen and monitor the borrower and typically have an informational advantage based on their long-term relationship with the borrower (Allen, Gottesman, and Peng, 2012). The lead arrangers choose the participant lenders and administer the loan/syndicate, whereas participant lenders essentially just fund the loan. Large loans are typically structured in multiple facilities. All facilities are covered by the same loan agreement; however, they may have different maturity or drawdown terms. One of the most obvious benefits of loan syndication has to do with a reduction in agency problems and informational asymmetries (Dennis and Mullineaux, 2000; Ivashina, 2009). See Wilson (1968) for a general theory of syndication and Pennacchi (1988) for a more general model of bank loan sales.

Namely, the VaR constraint requires that the ex-ante Sharpe ratio of bank j's portfolio is greater than ϕ, which is determined by the tolerance probability α.

The lead bank is risk neutral and chooses X_j to maximize expected return subject to the VAR constraint:

$$\max_{X_j} \ E(R'_j X_j) \tag{2}$$

$$\text{s.t.} \quad (e + RX_j)^2 \geq \phi^2 \sigma^2 X_j^2 \tag{3}$$

where (3) is derived from (1). By solving the maximization problem, the optimal loan size is given by $X^* = e/(\sigma\phi - R)$. Thus, the total lending amount in autarky is simply derived as NX^*.

B. Risk sharing through the syndicated loan market

The total lending amount can be increased by risk sharing through syndication of bank loans. In the syndicated loan market banks can trade a share of a loan. To model this, we assume loans are divisible and other banks can buy shares of the loan that bank i is lead-arranging. The amount of the share, s, is set as an exogenous parameter, and for simplicity we assume that it is equal among participating banks.

As a participant of project i, the participating bank receives return $R'_i - f$, where f denotes the spread between return earned by the lead arranger and a participant. It reflects compensation to lead arrangers to administering, screening, and monitoring the loan. In practice, f is determined in complex ways and may not have a simple accounting counterpart in the contractual terms of the loan. So, for simplicity we will assume f is constant across loans and, following Ivashina (2009), we will refer to it as a "fee." In return for accepting a discount of f relative to lead arrangers, participating banks benefit by the opportunity to invest in diversified projects at low cost.

Let a_j denote the lending to project j by lead bank j. Let Ω_j denote the set of banks who lead projects that bank j joins as a participant. Let l_j denote the size of Ω_j. Bank j's future wealth is thus

$$W'_j = R'_j a_j + \sum_{i \in \Omega_j} (R'_i - f)s \tag{4}$$

Given (4), banks diversify their idiosyncratic project risk by choosing optimal participation in the syndicates of other banks.

We make a standard assumption in portfolio theory that the return to project j, R'_j, has an idiosyncratic (diversifiable) and a common (non-diversifiable) component. We assume that R'_j is normally distributed with mean R and variance $\sigma^2 + \sigma_c^2$, where σ^2 and σ_c^2 denote the variance of the idiosyncratic and common components, respectively. Under these assumptions we have:

$$E(W'_j) = Ra_j + (R - f)sl_j \tag{5}$$

and

$$V(W'_j) = \sigma^2(a_j^2 + l_j s^2) + \sigma_c^2(a_j + l_j s)^2. \tag{6}$$

Note that the variance from the participation lending increases only linearly in size l_j if there were no common component σ_c. The variance of its own lending increases quadratically in size as a_j^2. This indicates that, when one considers diversification risks, then as banks' syndicated portfolios expand, the risk contribution from participation lending is lower than that of direct lending. Hence, bank's benefit of risk-sharing by participating in the syndicate loans.[10]

The bank's problem is to maximize $E(W'_j)$ by choosing a_j and l_j subject to the VaR constraint[11]

$$\frac{e + E(W'_j)}{\sqrt{V(W'_j)}} \geq \phi. \tag{7}$$

Since all banks face the same fee f and project attributes R, σ, and σ_c, the optimal choices a^* and l^* are symmetric across banks. The total amount of lending for project j is $X = a^* + l^* s$, and the total lending amount in this economy is NX. It is straightforward to see that the total lending amount is greater with syndication than in autarky when the lending amount X^* is sufficiently large. This is because, when X^* in autarky is large, a marginal shift from direct lending to syndicate lending increases the Sharpe ratio, which allows the bank to choose a greater

[10] Note that in the autarky case we assumed that banks could invest only in one project as lead arrangers. Thus, they were not able to spread investments across different loans and achieve benefits of diversification this way. In a simple world of only one project as lead-bank, syndication offers advantages by allowing banks to buy shares in other lead-banks' loans. We note that similar gains may be obtained by allowing banks to diversify by investing in different projects as lead arrangers. However, as we are interested in exploring the implications of different network topologies when allowing banks to interact through syndication, we maintain the assumption of only one project per bank as lead-arranger and abstract from the possibility of diversifying loans portfolios as lead arrangers.

[11] This maximization problem has a solution when σ^2 and σ_c^2 are sufficiently large relative to R. Note that l_j is chosen from the set of positive integers.

combined amount of direct and syndicate lending. Thus, in this case, the economy can benefit by the risk-sharing mechanism of bank syndicate formation.

C. Addition of bank capital shocks

Now we extend the model by incorporating a noise-ridden equity. We assume that banks' equity has an idiosyncratic stochastic component ϵ_j, so that bank j equity can be written as $e'_j = e + \epsilon_j$, where ϵ_j is normally distributed with mean 0 and variance σ_e^2 and independent across j (later we will also relax the i.i.d. assumption, allowing instead for part of the shock to be common across bank). We assume that ϵ_j is an exogenous shock, because this study is interested in how an exogenous shock on equity of a bank can propagate to other banks' behavior through syndicated loans. Under these assumptions, the VaR constraint is modified as:

$$\Pr(W'_j + \epsilon_j < -e) \leq \alpha. \tag{8}$$

We consider a situation where the equity risk realizes before the return risk realizes. There is a chance that the VaR constraint is violated for some banks due to the realized equity risk. In order to maintain the VaR constraint, some of these banks may find it optimal to withdraw from some syndicates that they intended to participate in. To keep things tractable, we assume that banks withdraw one hundred percent of their participation s.[12]

We also postulate that the lead bank is obliged to provide the withdrawn amount of lending additionally. Then, the withdrawal of a bank from a syndicate raises the risk exposure of the lead bank, inducing the lead bank to withdraw from another syndicate in order to meet the VaR constraint. We model this situation below.

Events realize sequentially as follows. First, the banks decide on a_j and l_j, and the total lending amount $X_j = a_j + \sum_{i \in \Omega_j} l_i s$ is committed to project j. Second, the idiosyncratic equity risk ϵ_j realizes. At this point, the participating banks may withdraw from the syndicate. If a bank withdraws, the lead bank of the syndicate either fulfils the pledged lending by increasing its own lending amount and adjusts its participation in other syndicates accordingly, or it decides to dissolve its own syndicate. As a commitment device, the bank is required to withdraw from all

[12]Thus, banks are not allowed to optimize their withdrawals in a similar manner as they optimize their initial investments.

the other loans when it dissolves its own syndicate. In the final stage, the investment return R'_j realizes.

Let $\Omega_{j,0}$ denote the set of projects that j decides to withdraw from. $\Omega_{j,0}$ is a subset of Ω_j and its size is denoted by k_j. Namely, k_j denotes the number of syndicated loans withdrawn by bank j. Also, let h_j denote the number of participants who withdraw from the syndicated loan that is led by bank j. That is, h_j is the number of times that bank j appears in the set $\cup_{i=1}^N \Omega_{i,0}$. Using these notations, bank j's wealth when the bank decides to maintain the syndicate is written as

$$W'_j = R'_j(a_j + h_j s) + \sum_{i \in \Omega_j \setminus \Omega_{j,0}} (R'_i - f)s, \tag{9}$$

whereas bank j's wealth is zero ($W'_j = 0$) when j decides to dissolve the syndicate.

The intuition behind the model is as follows. Implicitly, we assume that in the absence of equity shocks banks maintain the same syndicates (e.g., lending to the same borrowers) rationally taking into account project risk, hence each round we repopulate the model from the same distribution. However, once banks' equity shocks realize, some of them find it optimal to pull-back on their pre-commitments. To the extent that a withdrawal of a bank from a syndicate induces the lead arranger to adjust its own behavior (either commit additional funds to own syndicate and reduce participation in other syndicates or dissolve the syndicate), this causes ripple effects through the market.

D. Bank behavior

Second stage maximization (after ϵ_j and h_j realize). In this extended model with equity shocks, the VaR in the second stage ($\Pr(W'_j + \epsilon_j < -e \mid \epsilon_j) \leq \alpha$) is different from that in the first stage, because the equity risk realised: the denominator of the Sharpe ratio no longer includes σ_e^2, while the numerator is $e + \epsilon_j$ instead of e. Thus, bank j's decision in the second stage given h_j depends on the realized value of ϵ_j. When ϵ_j is sufficiently high, the bank maintains the participation l_j. When ϵ_j is low, it reduces $l_j - k_j$ or dissolves the syndicate loan. This can be seen as follows. Suppose that bank j experiences $h_j = 1$ (i.e., one participating bank withdraws from j's leading loan). It increases j's lending amount to project j from a_j to $a_j + s$, if j decides to maintain the syndicate. a_j was determined so that the VaR constraint in the first stage binds.

Thus, the increase to $a_j + s$ along with a decrease in l_j necessarily violates the first stage VaR (if the shock were known), because otherwise a_j was not the optimal decision (mean return to the leading loan is higher than the participating loan by the fee f). After observing $h_j = 1$, bank j decides to maintain the participation l_j if realized ϵ_j is sufficiently large. Otherwise, bank j decides to reduce its risk exposure by decreasing some participations (i.e., $k_j > 0$) or by dissolving its own syndicate altogether.

We can compute the policy of the bank as a threshold function of ϵ_j. For each realization of ϵ_j, given an equilibrium number of withdrawals h_j, bank j chooses k_j and whether to maintain its leading project or not in order to maximize $E(W'(k_j; a_j, l_j, h_j, \epsilon_j))$ subject to $\Pr(W'(k_j; a_j, l_j, h_j, \epsilon_j) < -e) \leq \alpha$, where the expectation of W' is taken over project risks. The wealth of bank j if the bank decides to maintain its own project is

$$W'(k_j; a_j, l_j, h_j, \epsilon_j) = R'_j(a_j + h_j s) + \sum_{i \in \Omega_j \setminus \Omega_{j,0}} (R'_i - f)s, \tag{10}$$

and $W'(k_j; a_j, l_j, h_j, \epsilon_j) = 0$ otherwise. Provided that the project is maintained, the bank's wealth follows a normal distribution with mean

$$R(a_j + h_j s) + (R - f)(l_j - k_j)s \tag{11}$$

and variance

$$\sigma^2((a_j + h_j s)^2 + (l_j - k_j)s^2) + \sigma_c^2(a_j + h_j s + (l_j - k_j)s)^2. \tag{12}$$

Thus, the bank's problem in the second stage (after ϵ_j realizes) is reduced to

$$\max_{k_j} R(a_j + h_j s) + (R - f)(l_j - k_j)s \tag{13}$$

subject to

$$\frac{e + \epsilon_j + R(a_j + h_j s) + (R - f)(l_j - k_j)s}{\sqrt{\sigma^2((a_j + h_j s)^2 + (l_j - k_j)s^2) + \sigma_c^2(a_j + h_j s + (l_j - k_j)s)^2}} \geq \phi. \tag{14}$$

The bank chooses to dissolve if the above maximum expected wealth does not achieve 0. We denote the maximized expected wealth $E(W'(k_j; a_j, l_j, h_j, \epsilon_j))$ by $W(a_j, l_j; h_j, \epsilon_j)$.

First stage maximization. A bank's problem in the first stage (before ϵ_j realizes) is $\max_{a_j,l_j} E(W(a_j,l_j;h_j,\epsilon_j))$ subject to $\Pr(W_j'+\epsilon_j < -e) \le \alpha$. $W(a_j,l_j;h_j,\epsilon_j)$ is determined from the second stage maximization, and the expectation is taken over ϵ_j and h_j. The distribution of equity shock ϵ_j is given exogenously. The distribution of h_j is endogenously determined in equilibrium. We assume that the equilibrium distribution of h_j is regarded as an exogenous environment by each bank. Let $p(h)$ denote the probability for h to occur, where $\sum_{h=0}^{\bar{h}_j} p(h) = 1$ in which $\bar{h}_j$ denotes the number of participants originally planned before the equity shocks realize. The bank's maximization determines an integer l_j, and a_j is determined by the VaR constraint with equality holding.

Figure 2 shows the timing of events in the first and second maximization stages, with the latter differentiated by the shaded region.

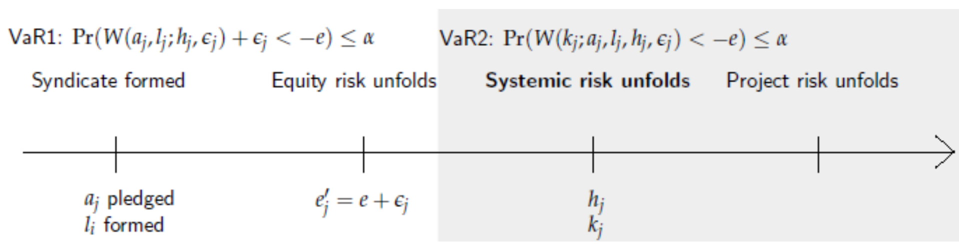


Figure 2. Timeline with bank equity shocks

Banks' policy functions. Bank's policy functions are a_j, l_j and $k_j(a_j,l_j,h_j,\epsilon_j)$. $q_0 = \Pr(\epsilon_j > \bar{\epsilon})$, where $\bar{\epsilon}$ is the minimum ϵ_j such that $k_j(a_j,l_j,0,\epsilon) = 1$, denotes the probability for bank j to withdraw from a syndicated loan even when there are no banks withdrawing from j's project.

E. Rational expectations equilibrium

Probability distribution $p(h_j)$ is determined by other banks' policy functions and the network structure. An equilibrium is the probability distribution $p(h_j)$ and the policy functions a_j, l_j and $k_j(a_j,l_j,h_j,\epsilon_j)$ such that the policy functions solve the bank's maximization problem given $p(h_j)$, and $p(h_j)$ is consistent with the bank's policy functions, the distributions of shocks ϵ_j and the network structure. The equilibrium maps a realization of the equity shock profile (ϵ_j) to an outcome (h_j) and (k_j). Thus, the equilibrium fluctuations of $\sum_j h_j$ and $\sum_j k_j$ are well defined.

III. Model simulations

In this section, we investigate the fluctuations of the numbers of withdrawals $\sum_j k_j$ and dissolutions. We are particularly interested in the tail part of the distribution of $\sum_j k_j$, which signifies the endogenous rare-event risk in the syndicated loan market that arises from the propagation effects of participations. By numerically simulate the rational expectations equilibrium defined above, we evaluate the rare-event probability at the systemic level. The simulations are conducted under three alternative network structures. First, we simulate a homogeneous-degree network, which corresponds to the benchmark model. Second, we simulate shock propagation in a network with uniform degree distribution. This corresponds to the weighted degree distribution of a network based on the Euclidean distance of banks' syndicated loan portfolios (this is based on the methodology of Cai, Saunders, and Steffen 2011). Third, we conduct simulations in an alternative network, constructed using directed links between the 82 most-active banks in our sample.

We also explore how the distributions of withdrawals and dissolutions change under different distributions of bank equity shocks, including when part of the shock is common across banks. The common equity shock captures an environment such as the 2008 subprime crisis, when many banks faced the prospect of capital shortfall at once. Specifically, we let ϵ_c denote the common component to the equity shock. Then, each bank j equity becomes $e'_j = e+\sqrt{\theta}\epsilon_c+\sqrt{1-\theta}\epsilon_j$; where $\epsilon_c \sim N(0, \sigma^2_{e_c})$, $\epsilon_j \sim$ i.i.d. $N(0, \sigma^2_e)$, and $\sigma^2_{e_c} = \sigma^2_e$. We assume that the banks observe realizations of e'_j, but they do not observe realisations of ϵ_c and ϵ_j independently. Namely, the banks do not know how much of the realized equity shock is caused by the loading on the common factor and how much is specific to their institution. As a result, they still solve the same optimization problem as when all of variation in e'_j is idiosyncratic. This mimics the environment of interbank market freezes in the U.S. and Europe following the subprime shock, when banks were essentially unable to accurately assess the solvency of other institutions. We conduct simulations for three alternative loadings of shocks on the common component: $\theta = 0$, $\theta = 0.05$, and $\theta = 0.50$.[13]

A. *Parameter choice*

We calibrate model parameters to match some aspects of the syndicated loan market. Table I shows calibrated parameters. We construct the networks using syndicated-loans transactions

[13]Note that $\theta = 0$ corresponds to the benchmark case of no common equity shock.

from Dealogic, including information on 2-SIC codes, deal nationality, and tranche amounts. The aggregate parameter calibrations are guided by information on mean and standard deviations of loans spreads (obtained from Dealogic), bank capital ratios (obtained from Bankscope), and default likelihood (obtained from Bloomberg). Specifically, from Dealogic we obtain tranche-level data on lead and participating banks, their role in the syndicate, tranche signing and maturity date, and interest rate spread on the loan, and percentage of loan amount allocated to each bank. We then merge it with the data from Bankscope on bank capital ratios (Bankscope item 18155), and with data on market based estimates of bank default likelihood (Bloomberg DRSK). In all, we get consistent coverage for syndicated lending made by the 82 most active/largest global banks in the years 2005-2007.[14]

We set σ to 15%, which corresponds to 2% default risk of the investment project j.[15] The total number of banks is set at 82, corresponding to the number of actively participating banks in our dataset. The typical loan has 6 participants. The size of equity is normalized to 1, and the standard deviation of equity risk is set at 1%. Thus, the equity risk is small enough not to cause default by itself. The size of a participant's share is set at 0.1.

Table I. Exogenous parameters

mean excess return	R	0.05
standard deviation of returns	σ	0.14
standard deviation of common returns shock	σ_c	0.01
equity (normalized)	e	1
standard deviation of idiosyncratic equity shock	σ_e	0.01
standard deviation of common equity shock	σ_{e_c}	0.01
VaR confidence level set to 99%	α	0.01
number of banks	N	82
average number of participants observed in the dataset	$\bar{l}$	6
loan amount per participant	s	0.1
weight of common equity component	θ	0, 0.05, and 0.50

For the computation of the policy functions, we start from an initial guess of fee f and a binomial distribution for $p(h)$ and then solve the bank's maximization problem numerically.

[14]Dealogic database has 706,385 observations from 2005 through 2007. We limit the bank sample to the largest 131 banks. Combined, they account for 63.98% of all observations during this sample period. However, we are able to match with Bankscope's balance sheet data only 82 banks.

[15]As we do not observe the life of the loan in Dealogic, only information at the origination, we do not have accurate information on the number of defaulted loans. Therefore, we use institution-level default likelihood measure from Bloomberg, which averages 2.3% for our sample of banks during the crisis period (year 2008).

Then we run simulations with the policy functions and the network and obtain simulated $p(h)$. Then we solve the maximization again using the simulated $p(h)$. The procedure is repeated until we observe convergence of $p(h)$. Once $p(h)$ converged, we check if $\bar{l}$ is the optimal number of participations a bank chooses. If $\bar{l}$ is optimal, then we obtain the solution. Otherwise, we update f and go back to the iteration on $p(h)$. Further details of the computation sequences are shown in Appendix A.

B. *Simulation results under homogeneous-degree network*

The benchmark model employs a homogeneous-degree network, in which the number of participants $\bar{l}$ is fixed constant across projects. Given the constant degree, the pair of a lead and a participating bank is drawn randomly.[16] With a finite number of banks $i = 1, \ldots, N$, we draw the network in our simulation as follows. First, we choose $\bar{l}$ participating banks randomly for bank $i = 1$. Next, we choose $\bar{l}$ participating banks for $i = 2$ randomly from the banks with the least number of existing participations (0 in this case). If the banks with 0 participation are less than $\bar{l}$, then we choose those banks and choose the remaining number of participation banks randomly from the banks with 1 participation. Then, we repeat the process for $i = 3, \ldots, N$.

No common equity shocks. As explained before, we model the equity shock as composed of two components, an idiosyncratic and a common component, so that bank j's equity is $e'_j = e + \sqrt{\theta}\epsilon_c + \sqrt{1-\theta}\epsilon_j$, where θ is the contribution of the common component of the equity shock. We start by simulating a situation with no common equity shocks, so that $\theta = 0$. Panel A of Figure 3 shows the distributions of the number of withdrawals and the number of dissolutions obtained by 10,000 Monte-Carlo simulations of the equilibrium with homogeneous-degree network and no common equity shocks.

With homogeneous-degree network, the withdrawal rate has a thin tail. This indicates that, while the market does exhibit some aggregate fluctuations arising from idiosyncratic equity shocks and interrelated share decisions, the likelihood of massive withdrawal events is very low.

Common equity shocks. Now we assume that a portion of the equity shock is common across banks. Importantly, banks know the aggregate distribution of the shock, but cannot identify what

[16] This type of network is sometimes called the configuration model in the network literature.

portion of e'_j is idiosyncratic or common. Panel B of Figure 3 shows the rate of withdrawals and the ratio of dissolved loans in the case of a common shock of 5% of banks' equity ($\theta = 0.05$). We now observe a slightly longer tail in the distribution of dissolutions.

Panel C of Figure 3 shows simulation results for the case of 50% of equity risk being common across banks (i.e., equal contributions from common and idiosyncratic components of equity shock so that $\theta = 0.50$). As the comparison to the case of 5% common shock in Panel B indicates, the equilibrium rate of withdrawals from syndication and the dissolution rate are quite sensitive to the correlation of equity shocks across banks. The propagation effects of syndicated lending are best gleaned by comparing the left-hand panels of the figure: the tail structure of the withdrawal distribution changes considerably. As bank equity shocks exhibit greater correlation, the withdrawal distribution begins to display fat tail features, with maximum withdrawal rate exceeding 30% in some cases.

C. Comparison to autarky

How does the aggregate risk seen in the previous network model compare to the case with no interaction across banks? To answer this question, we extend the autarky model in the previous section by incorporating an equity risk. The equity risk realizes after a bank decides its project size. The bank shuts down its project when it incurs in a large negative equity shock such that the project risk violates the VaR constraint given the realized equity shock. The project size is chosen to maximize the expected wealth under the VaR constraint such that the probability that the bank faces either the project dissolvement caused by the equity risk or insolvency caused by the project risk is less than 1%.

Since this is autarky, banks do not share the project risk by syndication. Hence, the number of dissolved projects follows a binomial distribution if the equity shock is independent across banks. When the probability of dissolvement is small, the number of dissolved projects asymptotes to a Poisson distribution. A simulated distribution for the number of dissolved projects with no common equity risk shown in the left panel of Figure 4 confirms this prediction. The center panel of Figure 4 shows the distribution when 5% of equity risk is common across banks. We observe a slightly extended tail distribution, but the difference to the case without common shock is not large. However, we observe a great difference when the common shock comprises 50% of equity

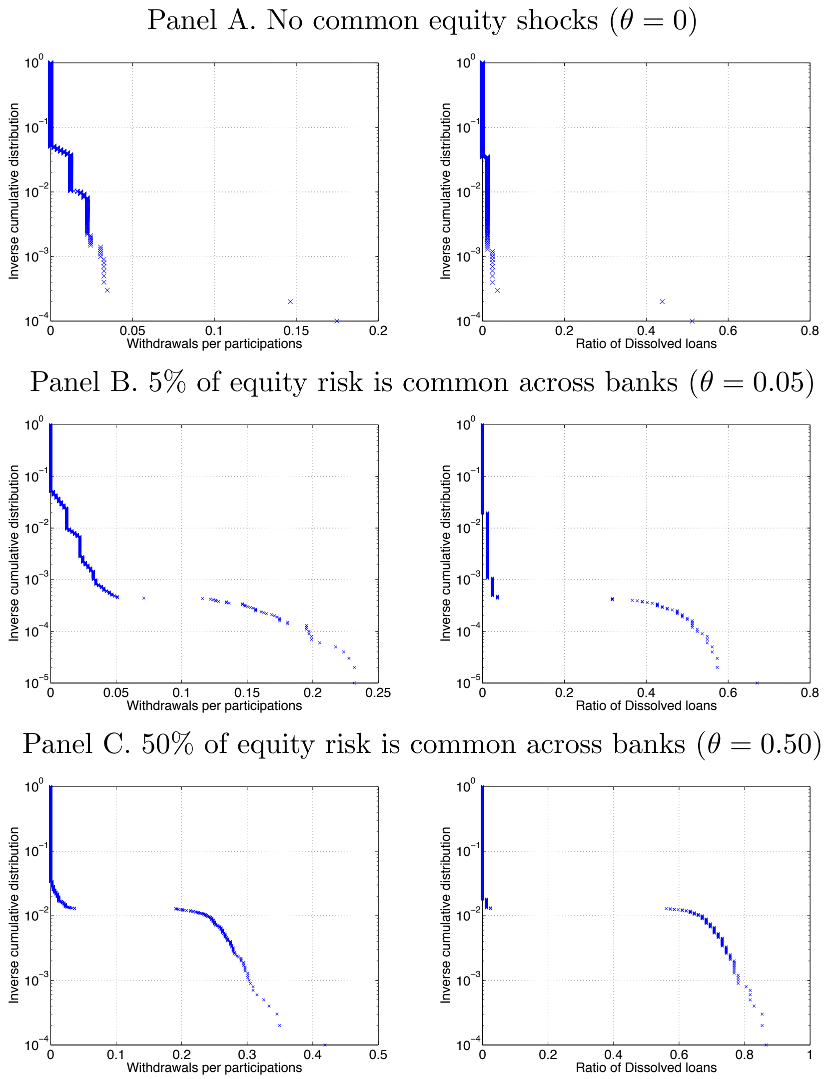


Figure 3. Distributions of withdrawals and dissolutions under different common equity risks across banks. *Left:* Rate of withdrawals $\sum_{j=1}^{N} h_j/(N\bar{l})$; *Right:* Ratio of dissolved loans to total loans N.

risk, as shown in the right panel of Figure 4. As can be seen, the tail events can induce 20% to 50% dissolvements of total projects.

The long tail under the large common equity risk can be understood as follows. Since banks maximize the expected wealth, they take as much risk as the VaR constraint allows them. Even though the idiosyncratic component of equity risk makes the banks' risk position heterogeneous, they are still similar enough relatively to the large common equity risk. Hence, many banks go under the threshold for dissolvements when a large negative common shock hits. This indicates

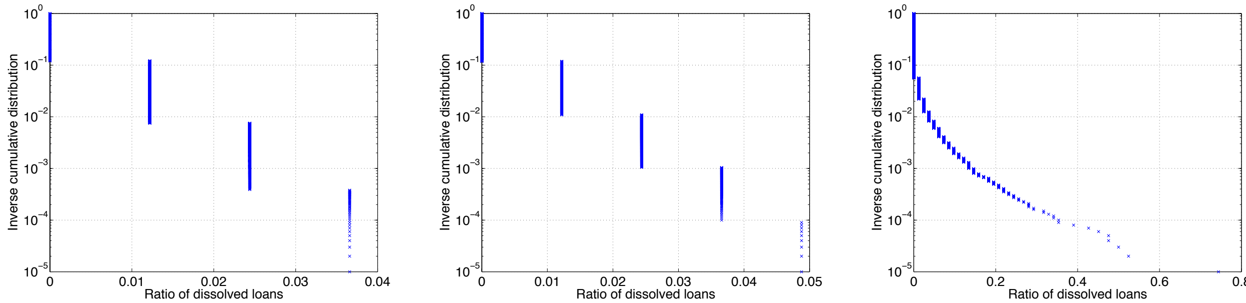


Figure 4. Ratio of dissolved loans to total loans in autarky. *Left:* No common equity risk across banks ($\theta = 0$) *Center:* 5% of equity risk is common across banks ($\theta = 0.05$). *Right:* 50% common equity risk ($\theta = 0.5$).

that, when the common shock is large enough, the aggregate risk of dissolvements exists and will show up as fat tails in the aggregate distribution even without interacting behavior of banks.[17] However, the interaction does transform the magnitude and distributional form of the aggregate risk. By comparing the distributions of dissolved loans with and without interaction under 50% common shock, we note that the interaction amplifies the extent of tail events. Also, by comparing the distributions under 5% common shock, we clearly observe that the aggregate tail event is present with interacting banks but not present with independent banks.

The relation of the realized common shock to the total number of dissolved loans also differs between the cases with and without interactions. Figure 5 illustrates this by scatter plots of the number of dissolved loans against the realized common shocks observed in simulations under a 50% common equity shock. The left panel shows the case without interaction, while the right panel shows the case with interaction through syndication.

When banks are independent, the tail events of large dissolution of loans are almost always associated with the realization of large negative common shocks. However, when banks are interacting through syndicated loans, this relation disappears. There are incidents of massive dissolution of loans even when the negative common shock is mild, and there are numerous incidents of few dissolutions even when the common shock is large and negative. Therefore, with interacting banks, a mildly negative common shock is a necessary condition for the tail aggregate risk, but whether the risk materializes or not depends on the configuration of idiosyncratic shocks

[17]This is similar to the "coherent noise" mechanism proposed by Sneppen and Newman (1997), where the maximization behavior of banks replaces the function of the extinction dynamics in the coherent noise mechanism.

falling on the bank network.

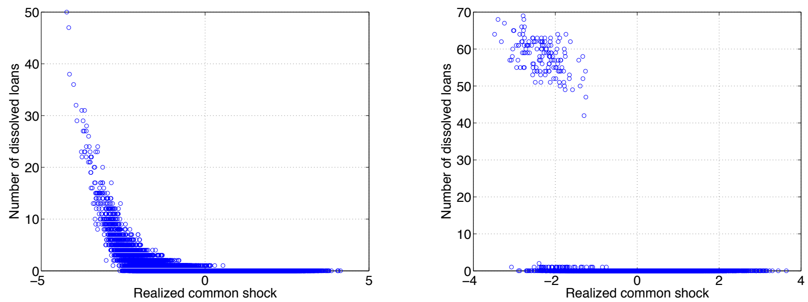


Figure 5. Scatter plots of realized common shocks and number of dissolved loans in simulations with 50% common equity risk ($\theta = 0.50$). *Left:* Autarky model *Right:* Homogeneous-degree network model.

D. *Heterogeneous degree network*

Next, we begin to incorporate additional empirical network features using market data. The first network structure we consider is based on banks' connectivity measured using commonalities in their syndicated loan portfolios. This measure of syndicated interconnectedness is based on Cai, Saunders, and Steffen (2011). Let $w_{i,j}$ denote the weight bank i invests in syndicate j such that for each bank $\sum_{j=1}^{J} w_{i,j} = 1$, where J is the number of deals in year t. We compute the Euclidean distance between bank m and bank n in the J-dimensional space:

$$d_{m,n} = \sqrt{\sum_{j=1}^{J} (w_{m,j} - w_{n,j})^2}. \tag{15}$$

If neither bank m nor bank n is a lead arranger in loan j, then $(w_{m,j} - w_{n,j})$ is not counted (i.e., set to missing).[18,19] Then a measure of the degree of connectedness for bank m with other banks through participation in common syndicates in year t is given by $deg_m = \sum_{n \neq m}^{N} d_{m,n}$.

[18]While Cai, Saunders, and Steffen (2011) compute the distance measure using syndicated portfolio commonalities based on cross-syndication in same industries(2-digit SIC code) or countries, we apply the same measure to cross-syndication at the loan level, j. This is possible because the degree of cross-syndication in this market is relatively high.

[19]Following Ivashina and Scharfstein (2010a), if a bank's role is an administrative agent, arranger, bookrunner, documenting agent, facility agent, mandated arranger, or syndication agent, the bank is designated as a lead arranger. In most cases, one lead arranger assumes most of these roles, while the database identifies other banks only as participants.

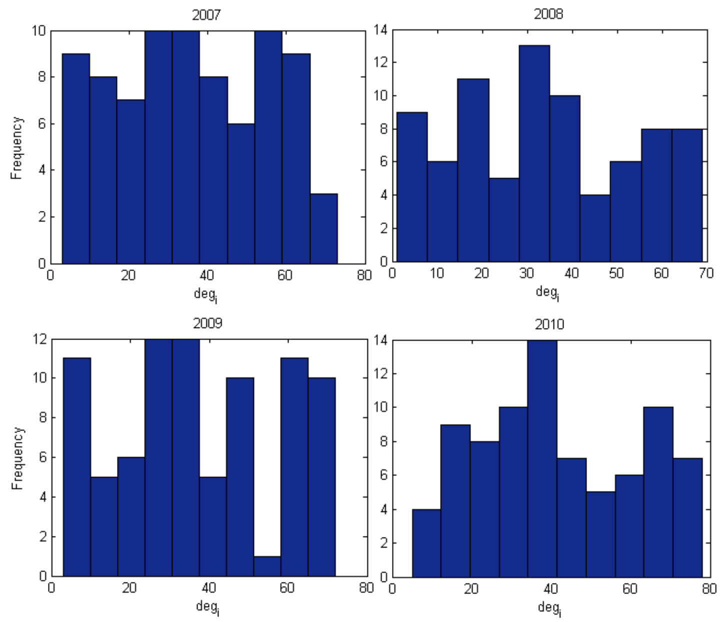


Figure 6. The figure shows histograms of degree distributions for selected years based on the Euclidean distance in banks' syndicated loan portfolios.

Figure 6 shows that the deal network constructed in this way exhibits a uniform degree distribution, which appears stable through the time sample. This implies that the banks are rather heterogeneous in terms of degrees, when these are computed based on syndicated loans portfolio weights. To mimic this network, we need to extend the model so that it allows a network with heterogeneous in-degrees (the number of banks participating in a project) and heterogeneous out-degrees (the number of projects that a bank participates in).

We extend the model by allowing the equity e_j and participation fee f_j to be heterogeneous across banks. Equity e_j is set proportional to the number of participants to the project led by j, while the equity of a bank with $\bar{l} = 6$ participants is normalized as $e_j = 1$ as in the homogeneous case. Fee f_j is calibrated so that bank j chooses the number of participations l_j as observed in the data. Bank j chooses less participations l_j when fee f_j is high. Finally, we redefine the withdrawal hazard function $p_j(h_j)$ to be dependent on j, since the probability of having h_j banks to withdraw from j's project depends on the number of initial participants and the network position of bank j. Thus, the rational expectations equilibrium requires each $p_j(h_j)$ to be equal to the simulated hazard function for each bank j.

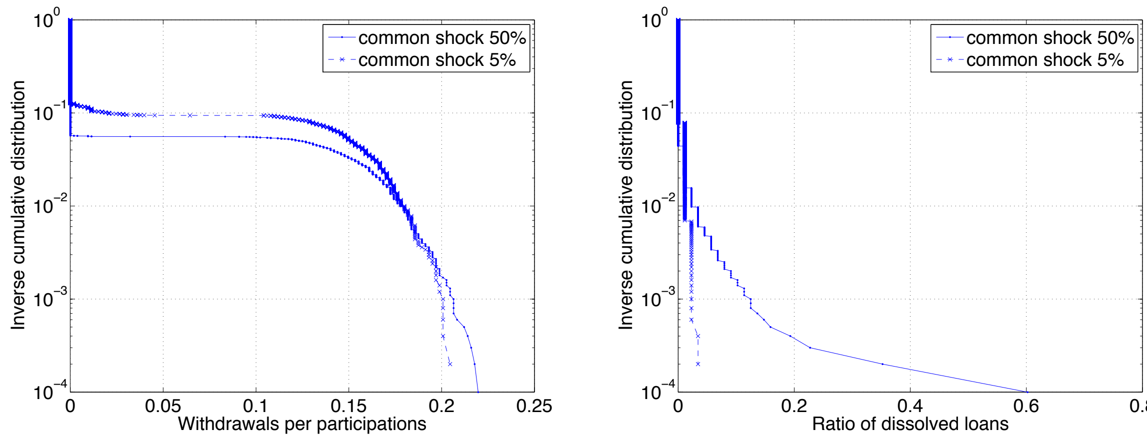


Figure 7. Heterogeneous degree network: *Left:* simulated histograms of the aggregate withdrawals. *Right:* simulated histograms of the dissolved loans.

Using the rational expectations equilibrium with heterogeneous degree network, we simulate the aggregate distributions of withdrawals and dissolutions. To mimic the empirical degree distribution above, we use the uniform distribution, and have an average number of participants equal to 6, which is the average number of participants observed in the data. Thus, in this simulation we draw a network of 88 banks, and have equal numbers of banks for degrees $1, 2, \ldots, 11$.[20]

Figure 7 shows the aggregate fluctuations under the heterogeneous degree network. Compared to the case of homogeneous degree distribution, we observe that the distributions do not have jumps. Moreover, we observe that the distributions of withdrawals and dissolvements both exhibit longer tails. We interpret this as an effect of heterogeneity in the degree distribution.

Importantly, the common component of equity risk does affect the tail risk greatly for the dissolved loans, but does not affect the tail distribution for the withdrawals as much. This implies that the aggregate adjustments of syndicated loans for the event of common equity shocks occur at the extensive margin rather than the intensive margin. In other words, syndicate dissolutions dominate as the margin of adjustment. This is consistent with the syndicated loan market collapse in 2008, when the average tranche size decline was moderate, only 13% (from $ 305 to 266 million), but the number of tranches declined from 15,070 to 11,556 (a 23% decline).

[20]Namely, there are 8 banks who lead projects with 1 participant, 8 banks with 2 participants, and so forth. This approach assures an average number of participants of 6.

E. Alternatively defined empirical bank network.

Next, we define an empirical bank network alternatively by focusing on whether each pair of banks has an arranger–participant relation at all. To define the network, we use the 2005 observations in our data set. We observe 82 banks who participate in any loan with a significant level of share which we define shortly. For each loan, we identify which banks take a lead role and which banks are participants. Then, we form a directed link from a participant bank to a lead bank. This structure is robust to cases with multiple lead arrangers, in which case each lead bank receives a directed link from participants.

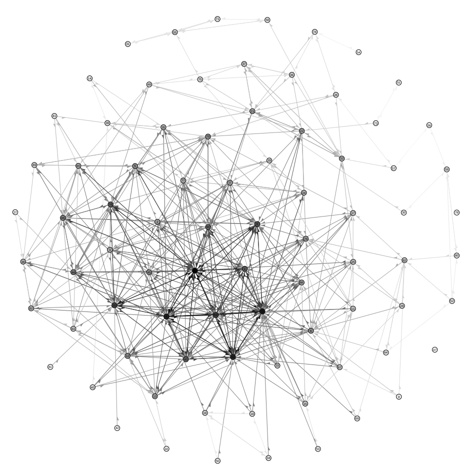


Figure 8. Directed network of banks in the syndicated loan market. A directed link is drawn from a participating bank to a lead bank.

We choose the threshold level of share to identify participating banks at 0.5% so that the average degrees of this network is comparable to the homogeneous case above (i.e., $\bar{l} = 6$). With this threshold value, we count 465 links among 82 banks. This empirical bank network is visualized in Figure 8, with the distribution of the number of participations by a bank shown in Figure 9. In the directed network of banks, this distribution can be called an out-degree distribution. Both figures point at a core-periphery network structure, with a core of highly connected banks surrounded by banks with only few syndicated connections.[21]

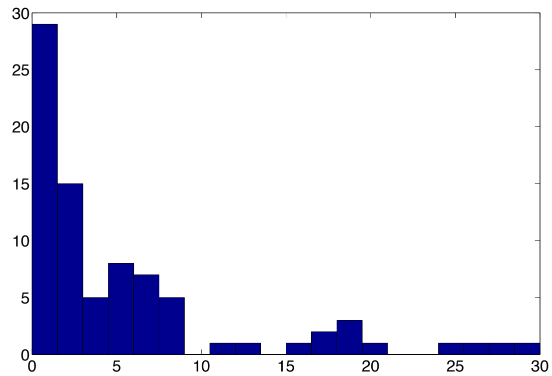


Figure 9. The out-degree distribution for the directed network

Figure 10 shows simulation results of aggregate withdrawals and dissolved loans when bank capital shocks propagate through this actual network. The left panel shows the simulated histograms of the aggregate withdrawals for the cases with 5% and 50% common equity shock. The right panel shows the simulated histograms of the dissolved loans.

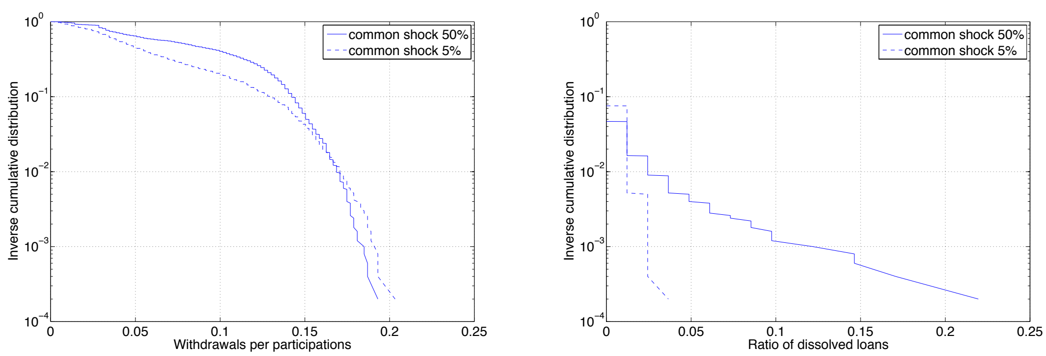


Figure 10. Simulated fluctuations in empirical lead-participant network: *Left:* simulated histograms of the aggregate withdrawals. *Right:* simulated histograms of the dissolved loans.

The distributions of withdrawals and dissolutions under this empirical network are similar to the distributions in the heterogeneous degree case. The aggregate fluctuations obey smooth distributions, reflecting heterogeneous degrees. The aggregate risks are evidently present: the

[21]In a different context, such core-periphery topology has been found to be a robust feature of interbank networks across different banking jurisdictions. See, for example, Soramaki, Bech, Arnold, Glass, and Beyeler (2007) for the Fed Funds market and Craig and von Peter (2013) for German banking system.

withdrawal rate can reach 15-20% and the dissolution rate exceed 50% for the case with 50% common equity shock. Similar to the heterogeneous degree case, we also observe that the tail distribution for withdrawals does not depend on the common component of equity risk, but the tail for dissolvements is significantly amplified by the common equity risk.

F. Two simple policy experiments

The model of syndicated lending nested in the empirical network of interconnected banks allows to run various experiments. Here, we present the results based on two simplified scenarios potentially of interest to policy makers and for future analysis. The first one tests the robustness of the market when a highly interconnected institution (in the syndicated loans market) fails; the second experiment studies the propagation of bank capital shocks assuming tighter regulatory capital requirements.

What about "too interconnected to fail?" First, we conduct an experiment on the effect of a targeted shock by using the heterogeneous degree network model. We select the bank which has the highest number of participations. Then, we shock that bank with an unexpected 10σ decline in equity; while all the other shocks are randomly drawn as in previous simulations. Figure 11 shows the aggregate fluctuations that arise from this large negative shock to the most interconnected bank. In the figure, we re-plot the benchmark distribution without attacks that were shown in Figure 7. We observe more incidents of withdrawal rates less than 0.15 in the case of an attack. This is a natural consequence of a forced distress on a bank. However, the tail distribution of the withdrawal does not exhibit any pronounced shift. Similarly, the distribution of dissolvement does not deviate from the benchmark case without attacks.

This result suggests that the failure of the most highly connected bank in this market may not necessarily trigger a large systemic event. In our model, a large number of dissolvements occur when a group of banks, each of which draws a negative equity shock, happen to be connected through syndicated loans. On one hand, the most highly connected bank is likely to be included in this connected group of damaged banks. On the other hand, it is not necessary that the most highly connected bank always ignites the propagation of dissolvements. Rather, it is likely that there are some other igniting banks in the group, because the group has a large number of banks. Our result suggests that, due to the latter effects, it is irrelevant to rare events whether the most highly connected bank draws an extremely large idiosyncratic shock. The rare systemic event occurs by the configuration of negative shocks on the network rather than who ignites the propagation.

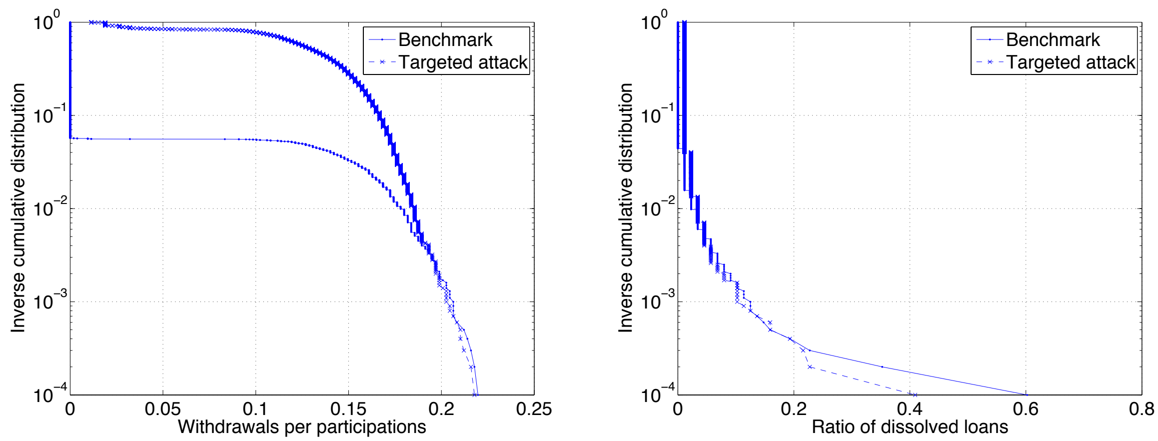
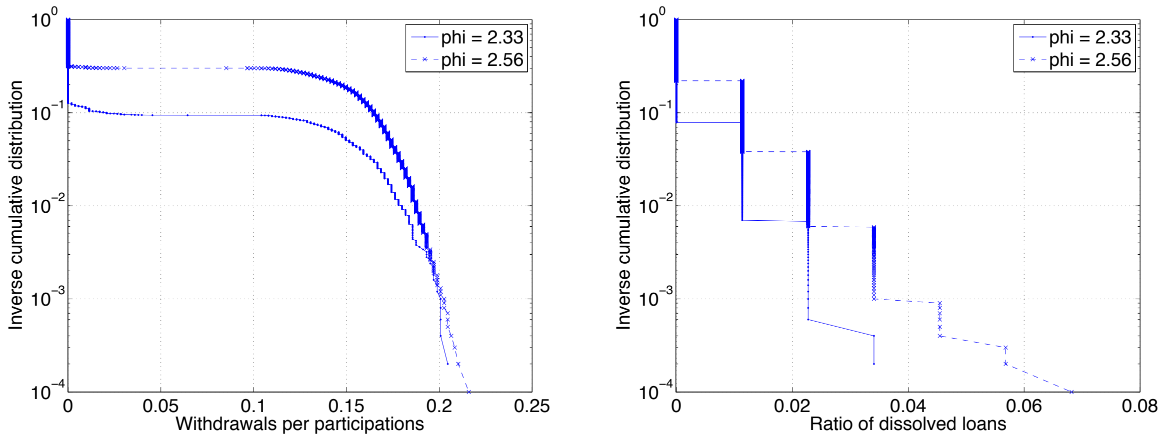


Figure 11. Targeted attack (assuming 50% common equity shock): *Left:* simulated histograms of the aggregate withdrawals. *Right:* simulated histograms of the dissolved loans.

Higher capital requirements / more conservative business models. We now turn to the implications of banks running more conservative business models due to higher capital requirements or other regulatory and market reasons. In a very simplified way, banks set aside capital in proportion to the VaR-based confidence interval of potential loss. The previous simulations were conducted assuming a 99.0% confidence interval of not breaching the capital threshold (ϕ=2.33). We now raise the confidence interval to 99.5% (ϕ=2.56). We perform this experiment under the heterogeneous degree network, since this is the network that best resembles the way banks are connected in the syndicated loan market from their asset side (i.e., based on portfolio commonalities based on cross-syndication to same borrowers). The distributions of withdrawals and dissolutions under the new tighter VaR constraint are shown in Figure 12.

The simulations suggest that a tighter VaR constraint leads to more incidents of non-zero aggregate withdrawals and dissolvements. However, conditional on non-zero withdrawals or dissolvements, the distributions exhibit little difference between the cases of tight and loose constraints. This is because the tighter VaR constraint produces two effects. First, it induces more withdrawals and dissolvement decisions in the second stage after the realization of equity shocks, if the risk-taking decision in the first stage is fixed. Second, the tight VaR constraint induces less risk-taking (by having a smaller project size a_j) in the first stage, as the banks anticipate more incidents of withdrawals and dissolvements upon the realization of equity shocks. These two countervailing effects result in the similar distribution of systemic events, as long as some withdrawals/dissolvements occur.

Panel A. 5% of equity risk is common across banks ($\theta = 0.05$)



Panel B. 50% of equity risk is common across banks ($\theta = 0.50$)

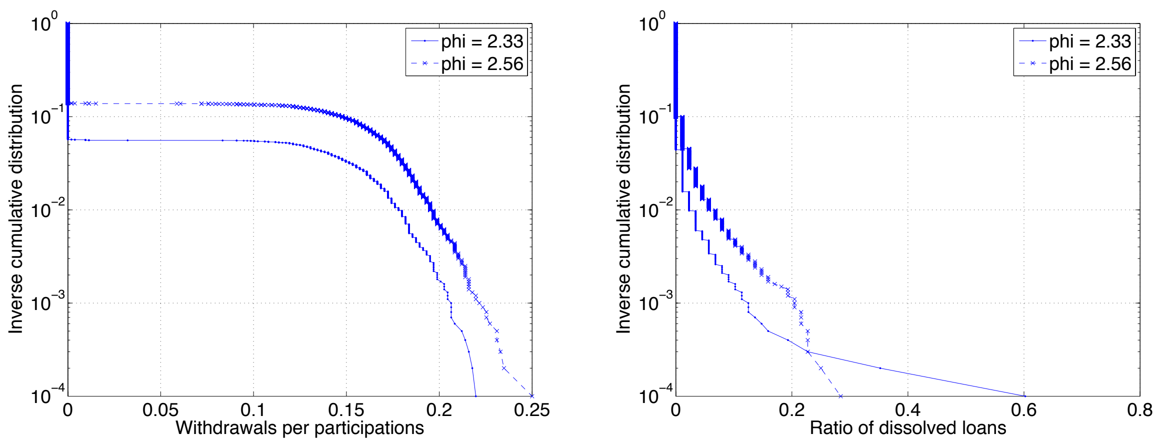


Figure 12. Tightening the VaR constraint. heterogeneous degree network. *Left:* rate of withdrawals $\sum_{j=1}^{N} h_j/(N\bar{l})$; *Right:* ratio of dissolved loans to total loans N.

IV. Conclusion

Syndicated lending has evolved into the main vehicle through which banks lend to large corporations. At the same time, the market is also quite volatile, with the volume of lending contracting by almost a half in 2008. We show that such rapid contractions in lending can arise when banks' reliance on a common risk management technology such as Value-at-Risk (VaR) is combined with their exposure to common borrowers through loan syndication.

We develop a a micro-founded model with capital constrained banks which are allowed to form syndicates. Syndicated loan market emerges naturally in equilibrium because forming connections with other banks by sharing exposures to common borrowers allows banks to diversify credit risk while also increasing lending in aggregate. However, particular market features, such as bank interconnectedness through common syndicates and distinct roles of lead arrangers, produce threshold effects that can lead to significant non-linearities when banks are hit with a shock to their equity capital.

Model simulations under different network topologies show that there are incidents of massive dissolution of loans even when the negative common shock is mild. Such tail risk appears strongest in the homogeneous-degree network, where we observe considerable non-linearity in the aggregate outcome: virtually no adjustments as well as an explosion in the number of dissolved loans are both possible in response to the same size negative common shock.

The distributions of the adjustment size in heterogeneous networks are smoother. These are network with uniformly distributed degrees and the empirical network of banks with directed links from participating banks of a syndicated loan to lead arrangers. Importantly, the degree distribution of the empirical directed network exhibits a core-periphery structure, which is more localized than a homogenous-degree network so might subdue systemic events.

We show the potential utility of the framework developed in this paper via two simplified policy experiments. In the first, we hit a bank which has the highest number of syndicate participations with a large unexpected negative equity shock. The simulation results show only a moderate increase in the probability of large withdrawals and syndicate dissolutions, suggesting that the failure of a highly interconnected bank may not necessarily generate a large systemic event in this market, given the empirical core-periphery network structure. In the second experiment, we tighten the VaR constraint to mimic an environment of higher required capital ratios. Simulation results suggest that the greater threat of violating the VaR constraint due to an equity shock is largely offset by the banks' preventive measure to unload risks beforehand. Both experiments show that banks' purposeful behaviors and rational expectations considerably affect the predicted likelihood of a systemic event in a bank network model. Still, further extensions of the model and simulation would be required before any conclusions about the market's resilience to financial sector shocks and implication for policies can be made with any confidence.

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A. Simulation computation strategy

Our main objective is to obtain the distributions of the number of withdrawals $\sum_j k_j$ and the number of dissolutions. We obtain the distributions by Monte-Carlo simulations of the equilibrium. The following is the computation algorithm for the case of the homogeneous-degree network, where the degree is given by $\bar{l}$.

1. Initialize f and the first-stage policy functions a_j, l_j
   (a) Solve for f so that $l_j = \bar{l}$
      i. Pick initial f and set $p(0) = 1$ (there is no withdrawals)
      ii. Solve the bank's first-stage maximization problem
      iii. Adjust f by bisection method until $l_j = \bar{l}$ is obtained
2. Set p as a binomial distribution with the probability for a bank to withdraw due to the equity shock and population l_j (this forms a "naive" expectation in which banks do not take into account the fact that withdrawal behaviors may be correlated)
   (a) Solve the second-stage maximization and obtain the expected wealth conditional on a_j, l_j, h_j
   (b) Solve the first-stage maximization
   (c) Update p until p converges
   (d) Check if l_j is still an optimal choice. If not, adjust f and repeat above
3. Simulations with network
   (a) Draw a random network with homogeneous degree l_j. Draw equity shocks ϵ_j.
   (b) With the policy functions and the network, compute the realized withdrawals and dissolutions.
   (c) Repeat for many times (10000) and obtain the simulated distribution of h
4. Compute a rational expectations equilibrium
   (a) Replace p with the simulated distribution of h

(b) Proceed to Steps 2 and 3 above

(c) Check if l_j is still optimal. If not, adjust f and repeat above