BANK FOR INTERNATIONAL SETTLEMENTS

BIS Working Papers

No 484

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Monetary and Economic Department

January 2015

JEL classification: E44, E52, G12, G20, E32.

Keywords: Syndicated lending, systemic risk, network externalities, value at risk, bank capital shocks, rare event risk.

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Bank capital shock propagation via syndicated interconnectedness*

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January 13, 2015

*We are grateful for the generous support of the BIS Research Fellowship Program. We also thank Tobias Adrian, Douglas Araujo, Dietrich Domanski, Ingo Fender, Blaise Gadanecz, Neeltje van Horen, Francisco Nadal de Simone, Iman van Lelyveld, Goetz von Peter, and the participants of the BIS Monetary and Economic Department Seminar (Basel, Switzerland, April 2013), the Conference on Network Approaches to Interbank Markets (Castellón, Spain, May 2013), and the Banque de France - ACPR - SoFiE conference on Systemic Risk and Financial Regulation (Paris, France, July 2014) for their comments and suggestions. We thank Sergei Grouchko and Michela Scatigna for excellent research support. Any views presented here are those of the authors and do not necessarily reflect those of the BIS.

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Bank capital shock propagation via syndicated interconnectedness

Abstract

Loan syndication increases bank interconnectedness through co-lending relationships. We study the financial stability implications of such dependency on syndicate partners in the presence of shocks to banks' capital. Model simulations in a network setting show that such shocks can produce rare events in this market when banks have shared loan exposures while also relying on a common risk management tool such as value-at-risk (VaR). This is because a withdrawal of a bank from a syndicate can cause ripple effects through the market, as the loan arranger scrambles to commit more of its own funds by also pulling back from other syndicates or has to dissolve the syndicate it had arranged. However, simulations also show that the core-periphery structure observed in the empirical network may reduce the probability of such contagion. In addition, simulations with tighter VaR constraints show banks taking on less risk ex-ante.

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I. Introduction

The erosion of bank capital and the subsequent deleveraging cycle in the aftermath of the 2008 Lehman collapse transmitted the credit crunch to the real economy. Such episodes underline the 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 a key 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 (Haas and Horen, 2012). Syndicated loan interlinkages among banks have also been shown to have a 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 that 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 study how shocks to bank equity capital affect banks' participation in the syndicated loan market. We build a micro-founded model of syndicated lending, taking into account the implications of several particular market features on the optimisation problem faced by banks. Banks operate subject to a value-at-risk (VaR) constraint, maintaining the level of capital to meet the risk profile of their loan portfolios. To the extent that capital requirements depend on VaR estimations, they provide one rationalization for the use of the VaR constraint. A related empirical finding by Adrian and Boyarchenko (2012) points to a close relationship

[1] For instance, as the market collapsed during the first year of the global financial crisis from approximately \$800 billion to \$300 billion in quarterly issuance volume (Gadanecz, 2011), international trade experienced the most sudden, severe, and globally synchronized collapse on record (Antonakakis, 2012). On the sensitivity of the 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 Haas and Horen (2012).

between credit tightening by banks and the risk-adjusted cost of leverage.[2] Thus, when banks face an erosion of their equity capital, they face a trade-off between selling liquid assets, issuing more equity, or reducing lending.[3] In this paper, we focus on the last of those three options. All solutions are derived assuming rational expectations.

We first show that a market for syndicated loans emerges naturally after allowing syndication in a model with risk-neutral banks that optimize their loan portfolios under a VaR constraint. Implicitly, we assume that in the absence of equity shocks banks maintain the same syndicates (e.g., keep rolling over lending to the same borrowers), rationally taking into account project risk. 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 its own syndicate and reduce participation in other syndicates or dissolve the syndicate), this causes ripple effects through the market.

Similar to Caccioli, Shrestha, Moore, and Farmer (2014), who study bank interconnectedness though overlapping portfolios, our model suggests that bank interconnectedness via co-lending in the syndicated loan market brings about a form of efficiency-stability trade-off. On the one hand, syndicated lending allows banks to diversify their credit risks, while also increasing lending in aggregate. On the other hand, complementarity in bank lending decisions due to dependency on syndicate partners can be a source of contagion.

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 micro-foundations 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.

The model further reproduces (agrees with) three stylized facts identified by the existing liter-

[2] Using data from from Q2 1991 to Q2 2012, Adrian and Boyarchenko (2012) estimate a correlation coefficient of 0.7 between the Chicago Board of Exchange Option Implied Volatility Index (VIX) and tightening of lending standards by US banks.

[3] See, for example, BCBS (2012) and BCBS (2013).

ature and the data from the crisis period.[4] First, the market is subject to very rapid adjustments in times of stress (the total volume of syndicated loans reported by Dealogic contracted by approximately 43% in 2008). Second, most of the adjustment takes place through a reduction in the number of loans rather than a typical loan size, that is along the extensive rather than the intensive margin.[5] 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.[6]

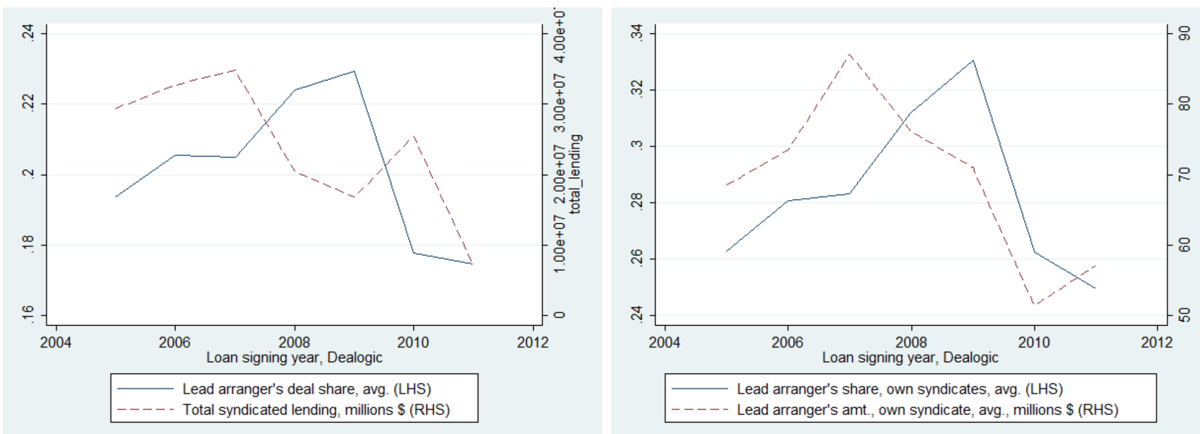


Figure 1. *Left:* Inverse relation of lead arrangers' share of total lending; *Right:* Asymmetric exposure of lead arrangers

Our 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 investment 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.[7] Danielsson, Shin, and Zigrand

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

[5] Specifically, from 2007 through 2009, about 80% of the contraction came from the reduction in the number of loans, and only 20% 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 million to $266 million.

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

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

(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.[8] Corsi, Marmi, and Lillo (2013) show analytically that the resulting combination of VaR technology with greater portfolio diversification can actually increase systemic risk. Similarly, using network simulations, Caccioli, Shrestha, Moore, and Farmer (2014) show that the combination of leverage with overlapping portfolios amplifies financial contagion.

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 and 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.

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 mutual syndicated lending to find that the 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 the syndicated loan market were less affected by

[8] More generally, a robust empirical relationship between bank capital and lending, as well as the ability of equity capital to serve as a buffer against negative shocks, are 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 global financial crisis (Caballero, Candelaria, and Hale, 2009).[9] 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.[10]

Our findings are four. First, simulation results indicate that syndicated interconnectedness matters for the propagation of bank distress in the system. With loan syndication, massive dissolution of loans can occur even when the negative common shock is mild; whereas it takes a large negative common shock to cause a substantial number of dissolved loans when banks are independent.[11] 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, where 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 the exogenous shocks themselves.[12]

Second, the aggregate effects of a common equity shock are present across networks with different shapes. We consider a homogeneous-degree network, a network with uniformly distributed degrees, and an empirical network based on Euclidean distance in banks' loan portfolios or based on the direct links to lead arrangers. The homogeneous-degree network corresponds to our benchmark model, in which each syndicate has the same number of participants. The uniform degree network is constructed using an indirect measure of connectivity based on the extent of overlaps in banks' syndicated loan portfolios.[13] The empirical network is constructed using directed links from participant banks to lead banks identified in the data prior to the global financial crisis.[14]

[9] In terms of geographic proximity, Haas and Horen (2012) use more traditional empirical tools to find that banks continued to lend more to geographically close countries, 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).

[10] 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.

[11] Not too surprisingly, simulation results show that a common, rather than idiosyncratic, component to bank capital shocks is the most evident driver of rare events in this market (these are defined as an aggregate rate of decline in loan syndication 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 syndicates shows a long tail.

[12] 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 as a key driver.

[13] Specifically, we look at the distribution of the Euclidean distance between each pair of banks based on their portfolio overlaps using the methodology of Cai, Saunders, and Steffen (2011).

[14] We look at new syndicated loans during year 2005 reported by Dealogic

Since the network structure of the syndicated loan market may change over time and may be sensitive to the sample selection of banks (e.g. our empirical network is based only on connections among banks which are themselves lead arrangers at least once during the sample period and meet a certain threshold in their lending contributions), we do not take a stance on the actual network structure of this market. Still, among different network structures, we find that the homogeneous-degree network is least stable. The equilibrium distribution of withdrawals and syndicate dissolutions in 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 dissolved syndicates (hereafter referred to as dissolved loans) or more than 50% dissolved. This points to a form of efficiency-stability trade-off characteristic of fragile market structures (in the spirit of Battiston, Gatti, Gallegati, Greenwald, and Stiglitz (2012) and Caccioli, Shrestha, Moore, and Farmer (2014)), should the actual empirical network approach this homogeneous case.

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

Lastly, we conduct two simple policy experiments. In one, we hit the bank with 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 very active bank may not necessarily generate a large systemic event in this market given the current empirical network structure. In the other experiment, we impose a tighter VaR constraint. Simulation results suggest that the greater chance of violating the VaR constraint due to an equity shock induces banks to take on less risky portfolios ex-ante.

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 discusses the results of the two experiments. Section V concludes.

II. Model

This section develops a micro-founded model of syndicated lending.[15] The basic setup resembles Danielsson, Shin, and Zigrand (2012), Corsi, Marmi, and Lillo (2013), Adrian and Shin (2014), and Caccioli, Shrestha, Moore, and Farmer (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, which in effect underwrites the loan. Lead arrangers follow a threshold rule: if hit by sufficiently large adverse equity shocks or if a critical mass of syndicate participants withdraw, then the lead arranger abandons the project. We refer to this process as "syndicate dissolution," understanding that in practice existing syndicates are not dissolved, but rather new syndicates are not formed. The modelling sequence reflects lead arrangers' forward-looking behavior, and can be thought of as "planned syndicate" formation absent exogenous shocks to own or participating banks' capital. It also reflects long-term relationships between lead arrangers and the borrower and that a firm's sequential refinancing in the syndicated loan market largely takes place through the same set of banks.

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. 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

[15] 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 syndicated 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 arrangers 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.

the variance of the idiosyncratic and common components, respectively. 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

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

where $V(\cdot)$ refers to variance. Namely, the VaR constraint requires that the ex-ante return-to-risk 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:

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

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

where (3) is derived from (1). By solving the maximization problem, the optimal loan size is given by $X^* = e/\left(\phi\sqrt{\sigma^2 + \sigma_c^2} - R\right)$. 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. A lead arranger in project j in effect underwrites the loan. For tractability, we assume that a bank can be the lead arranger in at most one project, so we use the notation bank j to indicate the lead arranger of a syndicated loan for project j.

In the syndicated loan market, banks can trade a share of a loan. To model this, we assume that loans are divisible and other banks can buy shares of the loan that bank j 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 j, the participating bank receives return $R'_j - f$, where f denotes the spread between return earned by the lead arranger and a participant. It reflects compensation to lead arrangers for 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 that 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 from the opportunity to invest in diversified projects at low cost.

Let a_j denote the lending to project j by lead bank j and s denote its lending to other projects. Let Ω_j denote the set of banks that 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:

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

where R'_i thus denotes gross return to bank j for a project in which the bank is a participant rather than lead arranger. Given (4), banks diversify their idiosyncratic project risk by choosing optimal participation in the syndicates of other banks. The fee f appears only in the return to participation lending (the second term), because the spread earned by arranging own loan compensates dollar-for-dollar for administrative and other costs that a bank incurs as the lead arranger. 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 l_j if there was no common component σ_c. The variance of bank's own lending increases quadratically in 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, banks benefit from risk-sharing by participating in the syndicated loans.[16]

The bank's problem is to maximize $E(W_j')$ by choosing a_j and l_j subject to the VaR constraint:[17]

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

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. The total lending amount with syndication is never smaller than that in autarky, NX^*. This can be shown as follows. When syndication is an option, a bank can always achieve the level of expected wealth achieved in autarky by choosing no syndication, $l = 0$. Therefore, the maximized expected wealth satisfies $Ra^* + (R - f)l^*s \geq RX^*$. Using this, we obtain $a^* + l^*s \geq X^* + (f/R)l^*s$. Thus, the economy can benefit by the risk-sharing mechanism of bank syndicate formation. Intuitively, loan syndication increases total lending, because a marginal shift from direct lending to syndicated lending increases the risk-adjusted returns, which, in turn, allows a bank to choose a greater combined amount of direct and syndicated lending.

C. *Addition of bank capital shocks*

As shown above, syndicated loans provide a means of risk-sharing among banks, and thus enhance the total lending amount in an economy. However, the syndication may pave the way for a new kind of aggregate risks through interlinked portfolios and interrelated decisions. In order to capture such risks, we extend the previous model by incorporating a noise-ridden equity. We assume that banks' equity has an idiosyncratic stochastic component ϵ_j, so that bank j's 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

[16] Note that in the autarky case we assumed that banks could invest in only 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 per 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 loan portfolios as lead arrangers.

[17] 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.

the shock to be common across banks). We assume that ϵ_j is an exogenous shock, because this study is interested in how an exogenous shock to bank's equity can be propagated 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 100% of their participation s.[18]

We also postulate that in order to proceed with the syndicate, the lead bank is obliged to compensate for the amount of any contributions withdrawn by other participants. Thus, the withdrawal of a bank from a syndicate raises the risk exposure of the lead bank, inducing the lead bank to withdraw from some another syndicates 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 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 which 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 this notation, bank j's wealth when the bank decides to maintain the syndicate is written

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

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 in 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 its 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 realized: 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 syndicated 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:

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

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 $\Pr(W'_j + \epsilon_j < -e) \leq \alpha$. $W(a_j, l_j; h_j, \epsilon_j)$ 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, the number of participants withdrawing from a syndicate arranged by bank 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.

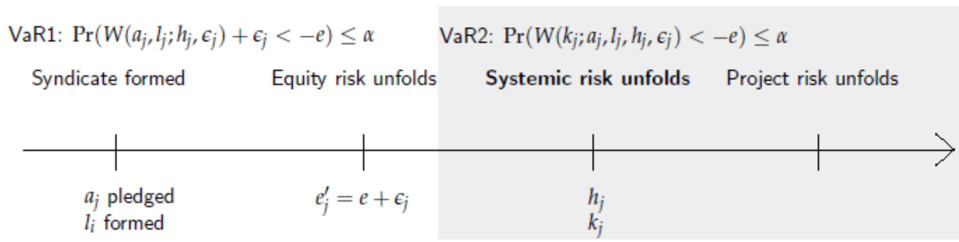


Figure 2. Timeline with bank equity shocks

Banks' policy functions. Banks' 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 of bank j withdrawal from a syndicated loan even when there are no banks withdrawing from j's project.

E. Rational expectations equilibrium

The probability distribution $p(h_j)$ is determined by other banks' policy functions and the network structure. An equilibrium is characterized by the probability distribution $p(h_j)$ plus 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 $p(h_j)$. The equilibrium $p(h_j)$, in turn, 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 the outcomes (h_j), withdrawals from syndicate j, and (k_j), withdrawals or own syndicate dissolution by lead arranger 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 simulating 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, j bank's 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 $\sigma^2_{e_c} = \sigma^2_e$.[19] 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 $\theta = 0.50$.[20]

A. *Parameter choice*

We calibrate model parameters to match broad features of the syndicated loan market. Table I shows calibrated parameters. We construct the networks using syndicated loan transactions from Dealogic, including information on 2-SIC codes, deal nationality, and tranche amounts. The

[19]Since the weight θ on the common component of equity shock is a free parameter, the standard deviation of ϵ_c is effectively a normalization parameter in the simulations. The situation where the standard deviations differ between the common and idiosyncratic components can be expressed by adjusting the value of θ.

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

aggregate parameter calibrations are guided by information on mean and standard deviations of loan 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, interest rate spread on the loan, and percentage of loan amount allocated to each bank. We then merge this 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 obtain consistent coverage for syndicated lending by the 82 most active/largest global banks in the years 2005-2007.[21]

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

The total number of banks is set at 82, corresponding to the number of banks in the merged dataset. The average number of participants is set to 6, based on the Dealogic sample once banks with average loan share of less than 0.5% are excluded. In the simulation, we set the starting value for the loan share per participant to 0.1, which leaves lead arranger with loan share four times that of a typical participant. The size of equity is normalized to 1, and the standard deviation of equity risk is set at 1% for both idiosyncratic and common components, which also keeps equity risk small enough not to cause default by itself. The standard deviation of common returns shock is also set at 1%. We set σ to 14%, which corresponds to 2.3% default risk of the investment project j. The average crisis-period default risk is calculated using market-based default likelihood measure (DRSK) from Bloomberg for the subsample of 50 banks (since the

[21] The 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 only 82 banks with Bankscope's balance sheet data.

DRSK measure is not available for all institutions in the sample, for example Bloomberg does not provide the measure for Japanese banks).[22]

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. Then we run simulations with the policy functions and the network and obtain simulated $p(h)$. Then we solve the maximization by 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 set to a constant across projects. Given the constant degree, the pair of a lead and a participating bank is drawn randomly.[23] 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 j bank'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 a homogeneous-degree network and no common equity shocks.

[22]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 an institution-level default likelihood measure from Bloomberg, which averages 2.3% for our sample of banks during the crisis period (year 2008).

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

With a 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 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 with 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 a restricted model without syndicated interconnectedness

How does the aggregate risk seen in the previous network model compare with the case with no interaction across banks? To answer this question, we consider a restricted case of the two-stage maximization problem by adding an additional constraint l=0 – that is by shutting off syndicate participation. The equity risk realizes after a bank decides its project size. The bank shuts down its project when it incurs 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 dissolution of the project due to the equity risk or insolvency caused by the project risk is less than 1%.

Since banks no longer share the project risk through syndication, the number of dissolved

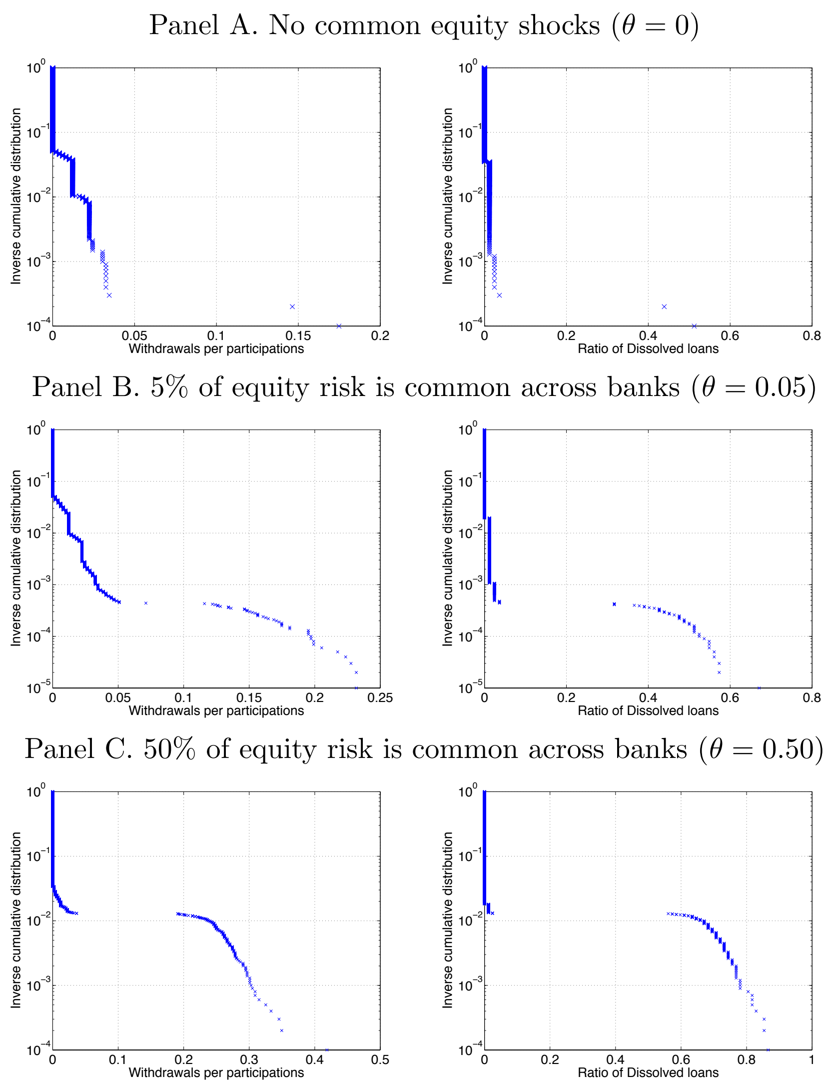


Figure 3. Distributions of withdrawals and dissolutions under different common equity risks across banks. *Left:* Rate of withdrawals $\sum_{j=1}^{N} h_j/(N\bar{l})$; *Right:* Ratio of dissolved loans to total loans N.

projects follows a binomial distribution if the equity shock is independent across banks. When the probability of dissolution 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-hand 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 from the case without common shock is not large. However, we observe a great difference when the common shock comprises 50% of equity risk, as shown in the right-hand panel of Figure 4. As can be seen, the tail events can induce 20%-50% of dissolutions of total projects.

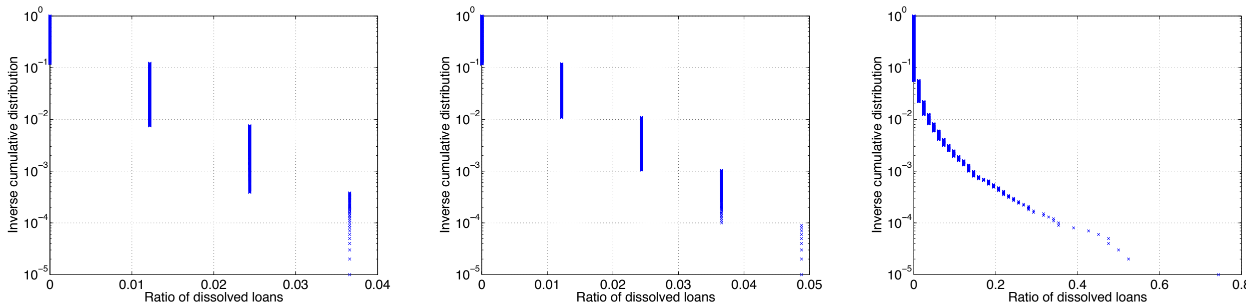


Figure 4. Ratio of dissolved loans to total loans in a model restricted by l=0: no syndicated interconnectedness. *Left:* No common equity risk across banks ($\theta = 0$) *Center:* 5% of equity risk is common across banks ($\theta = 0.05$). *Right:* 50% common equity risk ($\theta = 0.5$).

The long tail under the large common equity risk can be understood as follows. Since banks maximize the expected wealth, they take on 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 find themselves below the dissolution threshold when a large negative common shock hits. This indicates that when the common shock is large enough, the aggregate risk of dissolutions exists and will show up as fat tails in the aggregate distribution even without interacting behavior of banks.[24] 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 a 50% common shock, we note that the interaction amplifies the extent of tail events. Also, by comparing the distributions under a 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 through scatterplots of the number of dissolved loans against the realized common shocks observed in simulations under a 50% common equity shock. The left-hand panel shows the case without interaction, while the right-hand panel shows the case with interaction through syndication.

[24]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.

When banks are independent, the tail events of large dissolutions of loans are almost always associated with the realization of large negative common shocks. However, when banks are interacting through syndicated lending, 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 to the bank network.

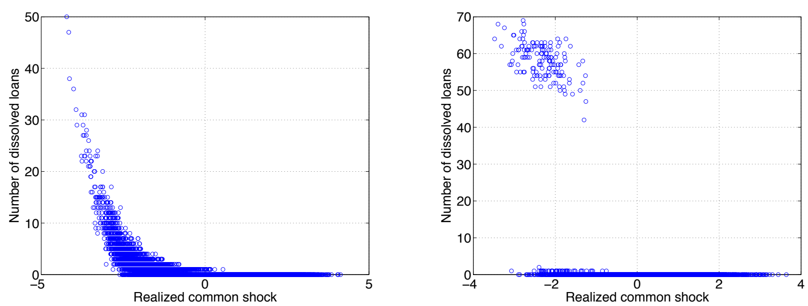


Figure 5. Scatterplots of realized common shocks and number of dissolved loans in simulations with 50% common equity risk ($\theta = 0.50$). *Left:* Model restricted to l=0: no syndicated interconnectedness *Right:* Homogeneous-degree network model.

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).[25,26] 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 $deg_m = \sum_{n \neq m}^{N} d_{m,n}$.

The deal network constructed in this way exhibits a uniform degree distribution, which appears stable through the time sample.[27] This implies that the banks are rather heterogeneous in terms of degrees, when these are computed based on syndicated loan 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 in 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. The fee f_j is calibrated such that bank j chooses the number of participations l_j as observed in the data.

Bank j chooses fewer participations l_j when the 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 withdrawing 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.

Using the rational expectations equilibrium with a 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 $1, 2, \ldots, 11$.[28]

Figure 6 shows the aggregate fluctuations under the heterogeneous-degree network. Compared

[25] 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.

[26] Following Ivashina and Scharfstein (2010a), if a bank's role is that of 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.

[27] See Figure 12 in Appendix B, which shows histograms of deg_m for selected years.

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

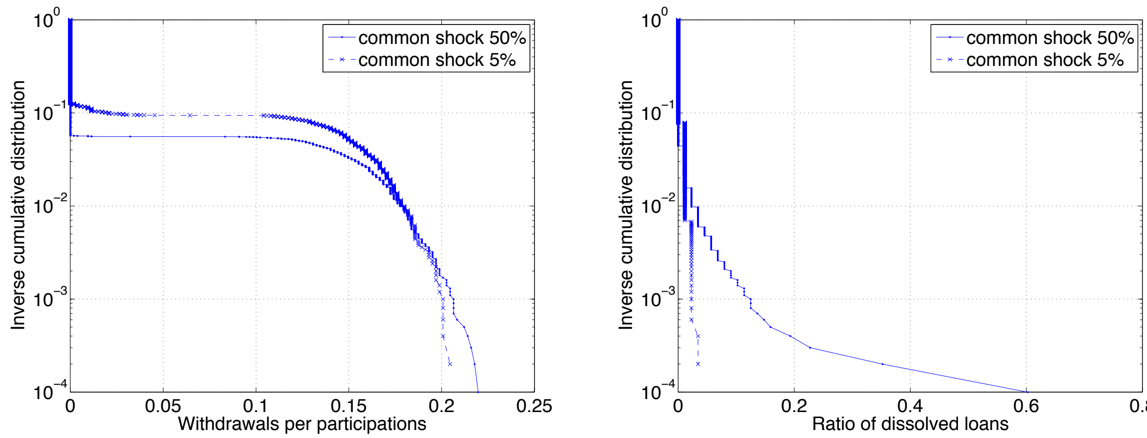


Figure 6. Heterogeneous-degree network: *Left:* Simulated histograms of the aggregate withdrawals. *Right:* Simulated histograms of the dissolved loans.

with the case of a homogeneous degree distribution, we observe that the distributions do not have jumps. Moreover, we observe that the distributions of withdrawals and dissolutions 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 million to \$266 million), but the number of tranches declined from 15,070 to 11,556 (a 23% decline).

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 Dealogic data on loans signings completed in 2005. We observe 82 banks that participate in any loan with a significant level of share, which we define below. 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. Hence, we depart from one lead arranger per loan assumption made in the model, with each node in the network instead representing a bank, but not necessarily a unique loan/syndicate.

Figure 7. 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 degree 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 7, with the distribution of the number of participations by a bank shown in Figure 8. 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.[29]

Figure 9 shows simulation results of aggregate withdrawals and dissolved loans when bank capital shocks propagate through this actual network. The left-hand panel shows the simulated histograms of the aggregate withdrawals for the cases with a 5% and a 50% common equity shock. The right-hand panel shows the simulated histograms of the dissolved loans.

[29]In a different context, such core-periphery topology has been found to be a robust feature of interbank networks across different jurisdictions. See, for example, **?** for the Fed Funds market, Craig and von Peter (2014) for the German banking system, and Fricke and Lux (2014) for Italian payment system.

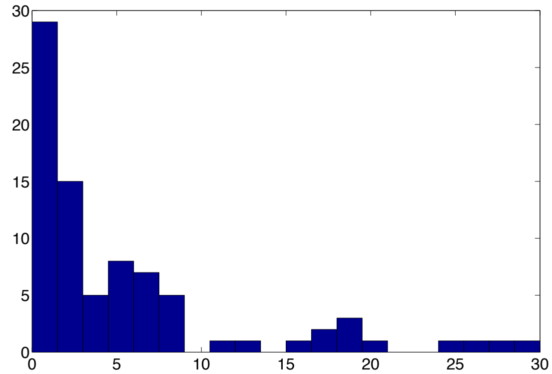


Figure 8. Out-degree distribution for the directed network

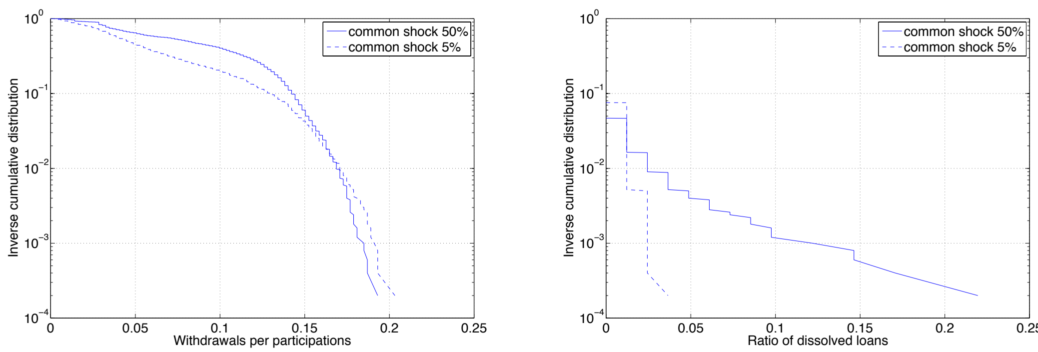


Figure 9. Simulated fluctuations in empirical lead-participant network: *Left:* Simulated histograms of aggregate withdrawals. *Right:* Simulated histograms of dissolved loans.

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 withdrawal rate can reach 15-20% and the dissolution rate can exceed 50% for the case with a 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 the fraction of dissolved loans is significantly amplified by the common equity risk.

IV. Two simple 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 loan market) fails; the second experiment studies the propagation of bank capital shocks assuming tighter regulatory capital requirements.

A. *What if the most active bank fails?*

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 10 shows the aggregate fluctuations that arise from this large negative shock to the most active bank. In the figure, we re-plot the benchmark distribution without the attacks that were shown in Figure 6. 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 to a bank. However, the tail distribution of the withdrawal does not exhibit any pronounced shift. Similarly, the distribution of dissolutions does not deviate from the benchmark case without attacks.

This result suggests that the failure of the most active bank in this market may not necessarily trigger a large systemic event. This may not be too surprising, given that the bank network considered here is not based on interbank lending/borrowing relationships. Furthermore, even for direct on-balance sheet interlinkages, the networks have been found to be robust. For example, Furfine (2003) conducts simulations using federal funds market data, Upper and Worms (2004) look at German interbank maker, while Mistrulli (2011) studies Italian payment system, with all finding some contagion but very limited system losses in response to a single bank failure.[30]

In our model, a large number of dissolutions occur when a group of banks, each of which draws

[30]This literature generally finds that for the systemic contagion to occur additional factors must be present on top of an idiosyncratic bank shock. For example, Upper and Worms (2004) conclude that a failure of one bank can affect sizeable impact only in association with large loss rates on interbank loans.

a negative equity shock, happen to be connected through syndicated loans. On the one hand, the most active bank is likely to be included in this connected group of damaged banks. On the other hand, it is not necessarily the case that the most active bank always triggers the propagation of dissolutions. Rather, it is likely that there are some other triggering banks in the group, because the group has a large number of banks. Due to these latter effects, our result suggests that the occurrence of rare events is not conditional on the most active bank drawing an extremely large idiosyncratic shock. Instead, the rare systemic event occurs through the configuration of negative shocks to the network, independent on which exact bank triggers the propagation.

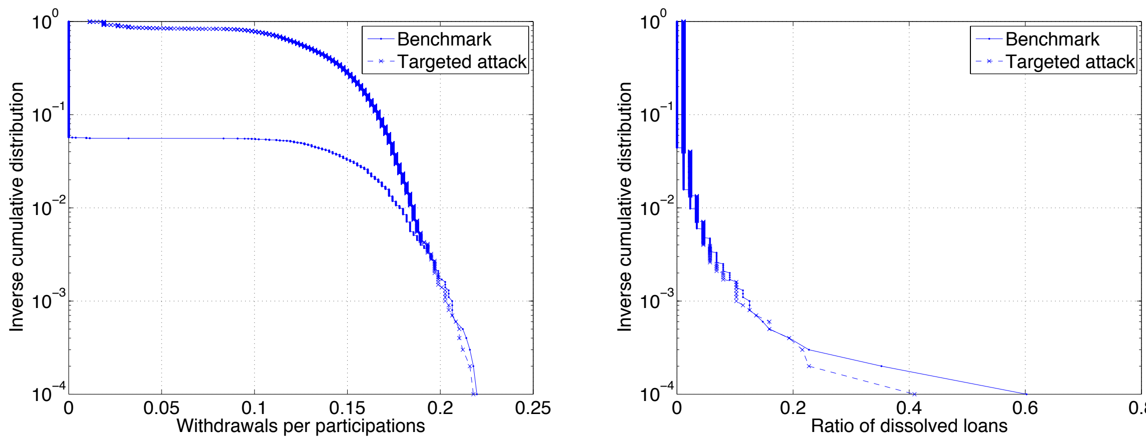


Figure 10. Targeted attack (assuming a 50% common equity shock): *Left:* Simulated histograms of the aggregate withdrawals. *Right:* Simulated histograms of the dissolved loans.

B. More conservative risk management.

We now turn to the implications of banks running more conservative risk management. In a very simplified way, banks can 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 implicit capital threshold (ϕ=2.33). We now raise the confidence interval to 99.5% (ϕ=2.56).[31] 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

[31] While the actual VaR constraint might be more strict, it is not desirable to push the threshold too close to the value of one because numerical implementation can become unstable. Still, this simplified framework is consistent with banks operating at the point at which they feel the restriction binding given the cushion they deem appropriate in terms of their risk management.

market from their asset side (i.e., based on portfolio commonalities derived from cross-syndication to same borrowers). The distributions of withdrawals and dissolutions under the new tighter VaR constraint are shown in Figure 11.

The simulations suggest that a tighter VaR constraint leads to more incidents of non-zero aggregate withdrawals and dissolutions. However, conditional on non-zero withdrawals or dissolutions, 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 dissolution 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 instances of withdrawals and dissolutions upon the realization of equity shocks. These two countervailing effects result in the similar distribution of systemic events, as long as some withdrawals/dissolved syndicates occur.

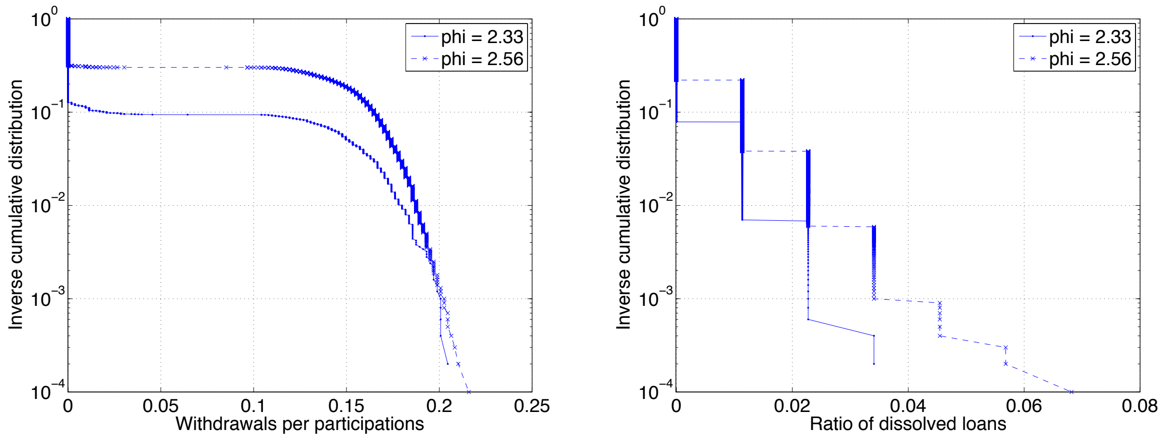
V. Conclusion

Syndicated lending has evolved into a key 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 micro-founded model with capital-constrained banks which are allowed to form syndicates. The 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 instances of large numbers of dissolved 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

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



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

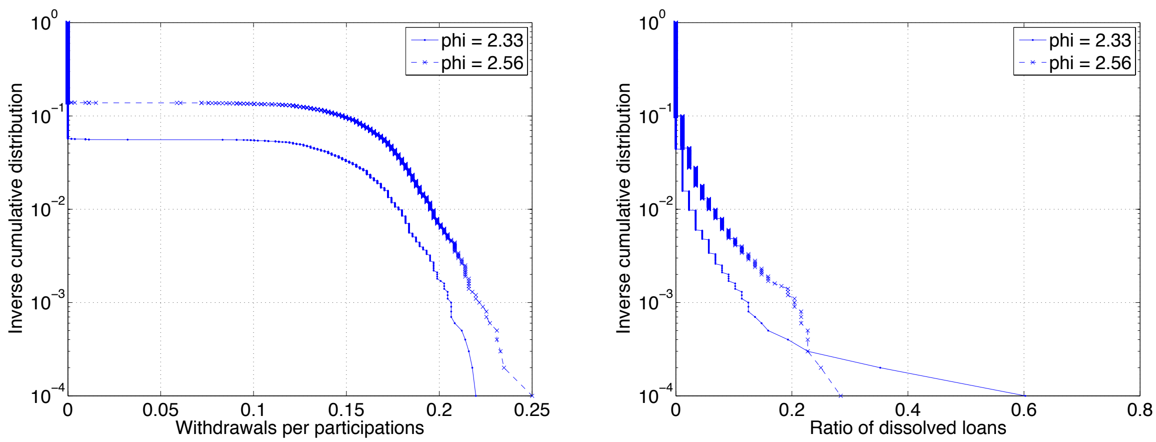


Figure 11. Tightening the VaR constraint. Heterogeneous degree network. *Left:* Rate of withdrawals $\sum_{j=1}^{N} h_j/(N\bar{l})$; *Right:* Ratio of dissolved loans to total loans N.

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 the network with uniformly distributed degrees and the empirical network of banks with directed links to lead arrangers from banks participating in a syndicated loan. Importantly, the degree distribution of the empirical directed network exhibits a core-periphery structure, which is more localized than a homogeneous-degree network, so might subdue systemic events.

We show the potential usefulness of the framework developed in this paper via two simplified experiments. In the first, we hit a bank that 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 sizeable pullback from lending and dissolved syndicates, suggesting that the failure of a highly active bank may not necessarily generate a large systemic event in this market – a sign of robustness, given the empirical core-periphery network structure.

In the second experiment, we tighten the VaR constraint to mimic more conservative risk management by banks. Simulation results suggest that the greater chance of violating the VaR constraint due to bank capital shocks is largely offset by the banks' preventive measure to unload risks beforehand. Both experiments show that banks' purposeful behavior 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 policy implications can be made with greater confidence.

References

Adrian, T., and N. Boyarchenko (2012): "Intermediary leverage cycles and financial stability," FRB Staff Reports 567, Federal Reserve Bank of New York.

Adrian, T., and H. S. Shin (2010): "Liquidity and leverage," *Journal of Financial Intermediation*, 19(3), 418–437.

——— (2014): "Procyclical Leverage and Value-at-Risk," *Review of Financial Studies*, 27(2), 373–403.

Agarwal, S. (2010): "Distance and Private Information in Lending," *Review of Financial Studies*, 23(7), 2757–2788.

Allen, L., and A. A. Gottesman (2006): "The Informational Efficiency of the Equity Market As Compared to the Syndicated Bank Loan Market," *Journal of Financial Services Research*, 30(1), 5–42.

Allen, L., A. A. Gottesman, and L. Peng (2012): "The impact of joint participation on liquidity in equity and syndicated bank loan markets," *Journal of Financial Intermediation*, 21(1), 50–78.

Antonakakis, N. (2012): "The great synchronization of international trade collapse," *Economics Letters*, 117, 608–614.

Battiston, S., D. D. Gatti, M. Gallegati, B. Greenwald, and J. E. Stiglitz (2012): "Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk," *Journal of Economic Dynamics and Control*, 36(8), 1121–1141.

BCBS (2012): "The policy implications of transmission channels between the financial system and the real economy," Basel Committee on Banking Supervision Working Paper, 20, Bank for International Settlements.

——— (2013): "Literature review of factors relating to liquidity stress - extended version," Basel Committee on Banking Supervision Working Paper, 25, Bank for International Settlements.

Berrospide, J. M., and R. M. Edge (2010): "The effects of bank capital on lending: What do we know, and what does it mean?," *International Journal of Central Banking*, 6(4), 5–54.

Bos, J. W., M. G. Contreras, and S. Kleimeier (2013): "The evolution of the global corporate loan market: A network approach," Mimeo, Maastricht University.

Caballero, J., C. Candelaria, and G. Hale (2009): "Bank relationships and the depth of the current economic crisis," *FRBSF Economic Letter*.

Caballero, R. J., and A. Simsek (2013): "Fire Sales in a Model of Complexity," *Journal of Finance*, 68(6), 2549–2587.

Caccioli, F., M. Shrestha, C. Moore, and J. D. Farmer (2014): "Stability analysis of financial contagion due to overlapping portfolios," *Journal of Banking & Finance*, 46(0), 233 – 245.

Cai, J., A. Saunders, and S. Steffen (2011): "Syndication, Interconnectedness, and Systemic Risk," NYU Working Papers FIN-11-040, NYU.

Carlson, M., H. Shan, and M. Warusawitharana (2013): "Capital ratios and bank lending: A matched bank approach," *Journal of Financial Intermediation*, 22(4), 663 – 687.

Chui, M., D. Domanski, P. Kugler, and J. Shek (2010): "The collapse of international bank finance during the crisis: evidence from syndicated loan markets," *BIS Quarterly Review*.

Cornett, M. M., J. J. McNutt, P. E. Strahan, and H. Tehranian (2011): "Liquidity risk management and credit supply in the financial crisis," *Journal of Financial Economics*, 101(2), 297 – 312.

Corsi, F., S. Marmi, and F. Lillo (2013): "When Micro Prudence Increases Macro Risk: The Destabilizing Effects of Financial Innovation, Leverage, and Diversification," Mimeo, Available at SSRN: http://ssrn.com/abstract=2278298.

Craig, B., and G. von Peter (2014): "Interbank tiering and money center banks," *Journal of Financial Intermediation*, 23(3), 322–347.

Danielsson, J., H. S. Shin, and J.-P. Zigrand (2012): "Procyclical Leverage and Endogenous Risk," LSE working papers, London School of Economics.

Dennis, S. A., and D. J. Mullineaux (2000): "Syndicated Loans," *Journal of Financial Intermediation*, 9(4), 404–426.

Devereux, M. B., and J. Yetman (2010): "Leverage Constraints and the International Transmission of Shocks," *Journal of Money, Credit and Banking*, 42, 71–105.

Fricke, D., and T. Lux (2014): "Core-Periphery Structure in the Overnight Money Market: Evidence from the e-MID Trading Platform," *Computational Economics*, doi:10.1007/s10614-014-9427-x.

Furfine, C. H. (2003): "Interbank Exposures: Quantifying the Risk of Contagion," *Journal of Money, Credit and Banking*, 35(1), 111–128.

Gadanecz, B. (2011): "Have lenders become complacent in the market for syndicated loans? Evidence from covenants," *BIS Quarterly Review*.

Gambacorta, L., and D. Marques-Ibanez (2011): "The bank lending channel: lessons from the crisis," *Economic Policy*, 26(66), 135–182.

Gambacorta, L., and P. E. Mistrulli (2004): "Does bank capital affect lending behavior?," *Journal of Financial Intermediation*, 13(4), 436–457.

Haas, R. D., and N. V. Horen (2012): "International shock transmission after the Lehman Brothers collapse: Evidence from syndicated lending," *American Economic Review*, 102, 231–237.

Hale, G. (2012): "Bank relationships, business cycles, and financial crises," *Journal of International Economics*, 88(2), 312–325.

Hale, G., C. Candelaria, J. Caballero, and S. Borisov (2011): "Global banking network and international capital flows," Mimeo, Federal Reserve Bank of San Francisco.

Hale, G., C. Candelaria, J. Caballero, and S. Borisov (2013): "Bank linkages and international trade," FRBSF Working Papers 2013-14, Federal Reserve Bank of San Francisco.

Hale, G., T. Kapan, and C. Minoiu (2013): "Crisis Transmission in the Global Banking Network," Mimeo, Workshop on the Economics of Cross-Border Banking, Paris, December 13-14.

Hattori, M., and Y. Suda (2007): "Developments in a cross-border bank exposure network," in *Research on global financial stability: the use of BIS international financial statistics*, vol. 29 of *CGFS Papers chapters*, pp. 16–31. Bank for International Settlements.

He, Z., and A. Krishnamurthy (2013): “Intermediary Asset Pricing,” *American Economic Review*, 103(2), 732–70.

Ivashina, V. (2009): “Asymmetric information effects on loan spreads,” *Journal of Financial Economics*, 92(2), 300–319.

Ivashina, V., and D. Scharfstein (2010a): “Bank lending during the financial crisis of 2008,” *Journal of Financial Economics*, 97(3), 319–338.

——— (2010b): “Loan Syndication and Credit Cycles,” *American Economic Review*, 100(2), 57–61.

Minoiu, C., and J. A. Reyes (2013): “A network analysis of global banking: 1978–2010,” *Journal of Financial Stability*, 9(2), 168–184.

Mistrulli, P. E. (2011): “Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns,” *Journal of Banking & Finance*, 35(5), 1114–1127.

Pavlova, A., and R. Rigobon (2008): “The Role of Portfolio Constraints in the International Propagation of Shocks,” *Review of Economic Studies*, 75(4), 1215–1256.

Pennacchi, G. G. (1988): “Loan Sales and the Cost of Bank Capital,” *Journal of Finance*, 43(2), 375–396.

Ruckes, M. (2004): “Bank Competition and Credit Standards,” *Review of Financial Studies*, 17(4), 1073–1102.

Sneppen, K., and M. Newman (1997): “Coherent noise, scale invariance and intermittency in large systems,” *Physica D*, 110, 209–222.

Upper, C. (2011): “Simulation methods to assess the danger of contagion in interbank markets,” *Journal of Financial Stability*, 7, 111–125.

Upper, C., and A. Worms (2004): “Estimating bilateral exposures in the German interbank market: Is there a danger of contagion?,” *European Economic Review*, 48(4), 827–849.

van Wincoop, E. (2013): “International Contagion through Leveraged Financial Institutions,” *American Economic Journal: Macroeconomics*, 5(3), 152–89.

Wilson, R. (1968): "The Theory of Syndicates," *Econometrica*, 36(1), 119–132.

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

B. Histrogram of degrees based on the Euclidean distance in loan portfolios

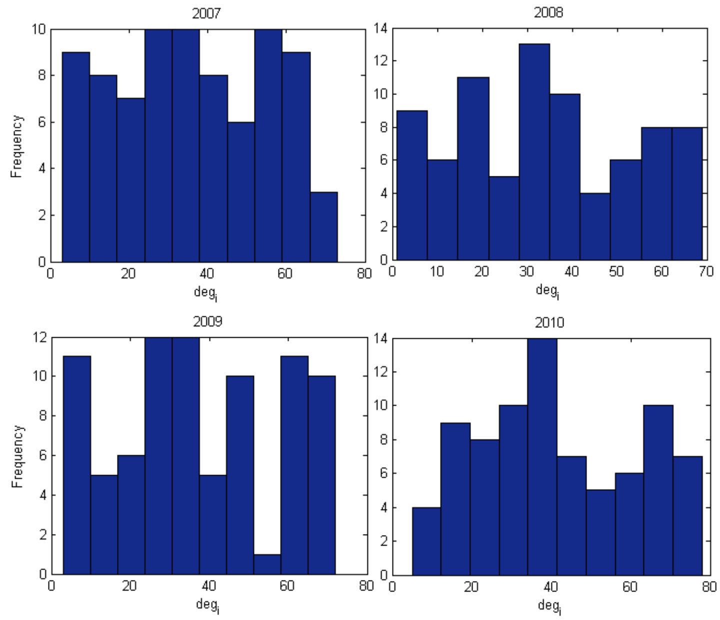


Figure 12. The figure shows histograms of degree distributions for selected years based on the Euclidean distance in banks' syndicated loan portfolios. This measure of syndicated interconnectedness is based on Cai, Saunders, and Steffen (2011).