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Interbank contagion and resolution procedures: inspecting the mechanism*

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Abstract

This paper develops a network model of a stylized banking system in which banks are connected to one another through interbank claims, which allows us to study the diffusion of default avalanches triggered by an exogenous shock under a number of different assumptions on the degree of interconnectedness, level of capitalization, liquidity buffers, the size of the interbank market and fire-sales. We expand upon the existing literature by embedding two alternative resolution mechanisms. First, liquidations triggered by either illiquidity or insolvency-related distress implying asset sales and compensation of creditors. Second, a bail-in mechanism avoiding bank closure by forcing a recapitalization provided by bank creditors. Our model speaks to how contagion dynamics unravel *via* illiquidity-driven defaults in the first case and higher-order losses in the latter one. Within this framework, we show how counter-party liquidity risk externality can be resolved and put forward a macro-criterion to assess the adequacy of the liquidity ratio introduced with Basel III.

JEL codes: D85, G28, G33

Keywords: Systemic Risk, Banking Network, Resolution Procedures
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1 Introduction

In the aftermath of the 2007-09 global financial turmoil, academics and regulators have made increasing efforts to advance our understanding of systemic risk. To this end, network techniques have been intensively applied to the analysis of contagion in the banking sector and the financial system in general.[1] The flourishing literature which ensued has developed rich theoretical models and empirical applications aimed at addressing a wide range of issues. Thus, counterfactual analyses on either real or artificial data have been employed to simulate interbank contagion leading to a systemic crisis under different assumptions on the size and the topology of the claims-obligations network linking the intermediaries' balance sheets, its degree of interconnectedness, the level of capitalization of financial institutions, the amount of liquidity in the market, the presence of a financial accelerator dynamics, and the degree of heterogeneity.[2] Supervisors has undoubtedly found in network models a powerful and flexible tool to identify and quantify the structural vulnerabilities of a financial system, and a guide to provide operational contents to the notion of macro-prudential regulation.

In this paper we aim to extend this approach by including one aspect of banking regulation that has received considerable attention on his own but has so far been overlooked in the financial network literature, that is the set of rules and prescriptions used to limit the real effects of a banking crisis through bank resolution procedures. As recently stressed among others by Haldane (2013), resolution procedures to address situations of banking financial distress are of critical importance and, along with the introduction of countercyclical capital surcharges and regulatory interventions on corporate governance and transparency, represent an area in which policy reforms are most needed.

Does the bank resolution regime matters for systemic risk and the propagation of contagion? If so, in what respect? And through which channels? In order to answer these questions, we device a simple network model to investigate the role of two alternative resolution mechanisms - bail-in and liquidation - and compare their influence on the system's resilience. We define as liquidation a regime in which a regulatory authority forces an insolvent bank to call in its interbank loans, sell all its remaining assets, use revenues to compensate creditors, and shut down immediately afterward. In an attempt to avoid the large direct and indirect costs associated with the sudden exit of a failed bank, however, international regulatory authorities are currently working to extend the available toolkit at their disposal by admitting the possibility that a fraction of the unsecured debt of a bank at the point of non-viability could be converted or written down.[3] Under a bail-in scheme, therefore, the regulator has the power to maintain a distressed bank as a going concern by restructuring its liabilities and converting them into equity, ensuring its survival without having recourse to tax-payers funds. While the main consequence of this procedure - that is, that the troubled bank continues to operate and remains an active node in the interbank network - is the same guaranteed by other resolution procedures like mandatory recapitalizations or government-sponsored bail-outs, it has the advantage of acting as an implicit insurance against the risk of insolvency provided by private creditors.

In what follows we recur to simulations to compare the contagion dynamics under the bail-in and the liquidation mechanisms in a network-based interbank market. This exercise allows us to distinguish between illiquidity-driven default cascades and higher-order losses as two separate key transmission mechanisms operating with different strength under the two alternative regimes. Furthermore, our analysis is conducive to a better understanding of the risk externality arising under the liquidation rule. Adapting a standard welfare economics

[1] See, among others, Upper (2007) for an introduction to the literature and models, Allen and Babus (2008) for a survey, and Gaffeo and Tamborini (2011) for a general perspective on the topic.

[2] An excellent review of the most recent literature is provided by Chinazzi and Fagiolo (2013).

[3] See, for instance, the Bank Recovery and Resolution Directive draft issued by the Council of the European Union on June 27^{th}, 2013.

approach, we show how policymakers can design a Pigouvian tax able to curb this externality by forcing banks to retain a liquidity buffer proportional to their interbank exposure, and we evaluate such a policy prescription in the light of the existing set of rules put forward by the so-called Basel III agreement. In particular, our analysis provides an additional macro-prudential criterion to evaluate the adequacy of recently introduced liquidity requirements - like the Liquidity Coverage Ratio (LCR), to be enforced from January 1st, 2015 - which have been instead conceived at first within a micro-prudential approach.

The remainder of the paper proceeds as follows. Section 2 motivates our analysis, reviews the existing literature on banking networks and provides a link with that on bank resolution. Section 3 outlines the model, while Section 4 presents results from Monte Carlo simulations and a policy experiment. Section 5 offers some final remarks.

2 Motivation and Literature Review

Network models of banking systems offer a number of attractive features. First, they allow to explicitly model banks as entities endowed with specific balance sheet characteristics. Second, they represent a flexible tool to examine a whole series of financial linkages among interconnected agents, like interbank loans, derivative exposures and payment systems. Third, they permit a direct investigation of the properties of complex network structures from either a static or dynamic perspective. In the context of banking crises, network models are deliberately tailored to investigate the property of the system under distressed scenarios due to the propagation of idiosyncratic shocks and contagion dynamics.

A fast growing literature has explored a wide range of critical issues according to a proof of principle perspective. For example, Nier et al. (2007) investigate by means of Monte Carlo simulations the extent to which the resilience of a prototypical interbank market depends on a combination of variables characterizing the network-wide topology, banks' characteristics in terms of net worth and interbank exposures, and market concentration. In particular, they show that there is a non-monotonic (inverted M or U-shaped) relation between the degree of interconnectedness and the number of total defaults after a single bank becomes insolvent. Interconnectedness acts first to strengthen contagion as it increases the number of channels (i.e., interbank links) through which an idiosyncratic shock can propagate through the network of counterpart exposures. Nonetheless, the residual shock passed on to any interconnected single institution becomes necessarily smaller as the number of links increases. Hence, interconnectedness also contributes to risk-sharing. As a matter of fact, beyond a certain threshold (or tipping point) this latter effect prevails and eventually enhances the resilience of the system. Using a similar simulation methodology, Gai and Kapadia (2010) shed lights on the so-called robust-and-yet-fragile property of modern banking systems. May and Arinaminpathy (2010) replicate these results in a close-form analytical solution using a mean-field approximation, while Gleeson et al. (2013) extend this framework to heterogeneous banks.

Other papers seek to provide a more accurate account of additional features of real-world banking systems. Iori et al. (2006), for instance, device a simulation model of the interbank market in which the lending and borrowing are endogenously generated rather than randomly allocated. They develop a stochastic environment in which banks respond to investment opportunities and to shocks affecting the liquidity of their assets, so that they resort to overnight interbank borrowing only when facing a temporary liquidity shortage. Hence, once initialized the adjacency matrix evolves endogenously according to each bank's demand and supply of interbank funds. Introducing heterogeneity in the quality of investment opportunities makes a highly connected system more prone to default cascades. Battiston et al. (2012a) study an economy with multiple sectors linked by credit-borrowing relationships in which a financial accelerator mechanism is at work. A high interconnectedness level proves to be detrimental to the robustness of the network when the financial distress of a bank is exacerbated by creditors requiring increasing interest rates. Financial accelerator-driven dynamics and risk-sharing act as counteracting forces, bringing about a non-monotonic relationship between interconnectedness and systemic risk. Finally, Krause and Giansante (2012) model a large banking system in which - consistently with the empirical evidence - the in-degree, out-degree and firm-size distributions exhibit fat tails scaling like a power-law. They also use simulated data to perform some regression exercises aimed at assessing the role played by the network's topological features, balance sheet positions and market competitiveness in determining individual failures and contagion.

To the best of our knowledge, however, the network-based literature on interbank systems has paid little if none attention to an explicit modeling of bank resolution, a critical topic that forcefully came under the spotlight as the recent crisis unfolded. As thoroughly discussed by Dewatripont and Freixas (2012), while bank resolution procedures have been subject to substantial scrutiny on their own in a well-established bankruptcy literature, we still have a very limited understanding of the impact that alternative regulatory responses to situations of financial distress may have from a systemic perspective.

Bank resolution is defined as an array of rules designed to reduce the negative impact of a bank's default - defined as a situation in which either an institution cannot meet debt payments, or its equity turns out to be negative - on the financial and real sectors of the economy. As part of the crisis management toolkit, four types of intervention can be considered as a policy response to banking distress. The first and most natural solution to restore the viability of an insolvent bank is that of mandating shareholders to recapitalize it through a direct injection of new equity, or to sell part of the bank's assets to pay off current liabilities, under penalty of suspension of the banking license. Although these options have the advantage of ensuring transparency and ex-ante incentive-compatibility, they are hardly feasible in times of systemic crisis and are subject to well-known problems of inter-temporal inconsistency. That is why in many cases troubled institutions have been bailed out by cash injections and/or explicit guarantees financed by the government budget. The scope of public intervention during the last crisis has been huge - in net terms, in June 2012 the exposure of the US government towards domestic banks amounted to \$1.2 trillion, while the equivalent figure in the EU was \$0.85 trillion - and it is becoming increasingly clear that there are severe downsides associated with it. Such an approach involves huge taxpayer transfers, it could bring about fiscal imbalances and, last but not least, it perversely affects banks' expectations and incentives for risk taking, compensation and dividend policies. In order to shield taxpayers from bank losses and curb moral hazard phenomena, resolution authorities are currently considering to expand their statutory powers to provide alternative means of prompt recapitalization and avoid the liquidation of a distressed credit institution by imposing a bail-in, that is a mandatory write-down or conversion to equity of its unsecured debt up to a minimal viability threshold. The implementation of such a power requires a careful outlining of the set of debt instruments to which restructuring applies, a clear order of priority according to which different types of claimholders will be asked to bail-in, a transparent and consistent definition of insolvency-related triggers, and the characterization of viability thresholds (Zhou et al., 2012). As a last option, authorities can abandon the objective of keeping the distressed bank as a going concern and order its final liquidation through a formal bankruptcy procedure. Such a procedure typically involves the substitution of the management team with an official receiver who is in charge of selling all the bank's assets, using proceeds to compensate creditors, and the closure of the firm.

Of course, it is of paramount importance to provide a well-identified framework to understand the pros and cons of different resolution options. In particular, this argument calls for an assessment not only of the micro-prudential implications (defined in terms of moral hazard and depositors' coordination to run away from the bank) associated to each one of them, but also of the extent to which the resilience of the whole banking system may be affected by regulatory choices. The goal of this study is precisely that of enhancing our understanding of issues related to the systemic risk buildup under two of the resolution regimes recalled above - namely, bail-in and liquidation - and to shed light on the policy actions required to tame contagion in these circumstances.

By adopting a micro-prudential approach, in fact, there seem to be some substantial benefits from keeping alive a bank in distress, given that this would permit to preserve specific borrower-lender relationships, avoid disorderly liquidation, minimize the risk of costly litigation and renegotiation of the bank's contracts, and preserve access to credit. The macro-prudential implications are far less obvious and have yet to be fully investigated, however. Forced liquidation of failed banks imposes a negative network externality on neighbor banks. Such externality arises because the troubled institution calls in interbank assets, which represent liabilities for some other banks. The latter ones may fail as well if they do not have enough liquidity to cope with this unexpected fund withdrawal. From a systemic perspective, therefore, the spread of such funding shocks throughout the network may amplify the severity of default cascades. Nonetheless, each liquidated bank is effectively removed from the system, and thus can no longer contribute to fuel contagion via second-order losses. Such a channel remains open whenever a distressed bank is kept as a going concern by a mandatory bail-in, and it represents an additional transmission mechanism which has a purely systemic dimension. We will show how these two dynamics interact to determine the system-wide degree of disruption, by analyzing the extent to which their relative strength depends on the structure of the banking system.

Given that the final goal of a regulatory agency is that of deploying damage-control actions calibrated on the chosen resolution mechanism, our analysis yields an interesting byproduct in terms of welfare. It turns out that a key issue in the context of the liquidation regime is the management of the counterparty liquidity risk. Indeed, sudden withdrawals of existing lines of credit provided through the interbank market when distressed banks are shut down work as unexpected liquidity shocks for the viable part of the system. In addition, banks may have an incentive to recur to short-term funding beyond what would be socially desirable and, as discussed in Perotti and Suarez (2011), there is not any automatic mechanism such that an individual bank will internalize the system-wide effect generated by this behavior. As observed by Acemoglu et al. (2013), this creates the potential for a financial network externality, which arises whenever banks choose a level of liquidity that allows them to hedge against their risk of default on the one hand, but below the socially optimum that would allow them to internalize the costs their default put on the system as a whole on the other one. We argue that one possible solution to align the social and private costs of banking bankruptcy is to use liquidity requirements as a discipline device operating as a Pigouvian tax.

3 The Model

Our model is tailored to simulate default avalanches triggered by an exogenous shock in an interbank market, with the aim of describing how the resilience of the system changes under the bail-in and the liquidation resolution procedures presented in the previous section. More specifically, we attempt to clarify the extent to which these different mechanisms affect the probability of contagion, and to measure how their relative impact changes as we gradually alter the degree of interconnectedness of the network, the level of capitalization of banks and the size of interbank exposures.

In the three remaining parts of this Section we present the network generation process of a stripped-down interconnected banking system, the shock-transmission mechanisms spreading contagion, and the parameters' calibration employed in simulations, respectively. We characterize banks via their balance sheets, and model interactions in terms of the web of directed and weighted links representing financial claims among interconnected institutions. We work with a semi self-contained system in which core liabilities are (exogenously) given by retail deposits, while every other non-core funding source (Hahm et al., 2013) goes through a broad definition of interbank operations. Thus, in what follows the term "interbank market" is just a short-cut for a set of instruments comprising overnight transactions, short-term and long-term interbank debt and wholesale funding.

3.1 Setting Up The Banking Network

Let us consider a set $n = 1, ..., i, .., n$ of banks. We assign to each bank $i \in n$ a deliberately oversimplified balance-sheet so that a bank asset structure is made up as depicted in Table 1.

Table 1: Bank Asset structure

Assets	Liabilities
A_i	NW_i
L_i	B_i
	D_i

A_i=External Assets, L_i=Interbank Assets
NW_i=Networth, B_i=Interbank Liabilities, D_i=Retail Deposits

The network is constructed in the following way. First, we create a weighted liability matrix X^l of mutual exposures. This is a n-by-n matrix whose X^l_{ij} elements specify the amount of money borrowed by bank i from bank j. By construction, this is equal to the amount lent by bank j to bank i. In equilibrium aggregate borrowing must be equal to aggregate lending. Each element X^l_{ij} takes up a positive value with a given probability p. For the purpose of the present paper, we concentrate our analysis on a homogenous banking system. Banks are approximately of the same size, have similar balance-sheets and share the same probability p of being connected to one another.[4]

Once X^l is in place, the interbank entries of each bank are obtained according to these rules: $i)$ $B_i = \sum_{j=1}^{n} X^l_{ij}$ (horizontal summation) where B_i is the total interbank assets of bank i and $ii) L_j = \sum_{i=1}^{n} X^l_{ij}$ (vertical summation) where L_j is the total interbank liabilities of bank j. Finally, once we have retrieved B_i and L_j $\forall$ i and j from X^l, we built each bank asset structure as explained in Table 2.

β captures the leverage ratio measured as tangible equity (net worth) over tangible assets. The parameter α defines the size of each bank's exposure on the interbank market. A few remarks are worth noticing. First, let us stress that each bank i's balance sheet hinges upon total interbank liabilities B_i.[5] Let us note that interbank assets (L_i) are endogenously determined according to the liability matrix, as in Gai and Kapadia (2010) or Gai et al. (2011). For low

[4]Technically, the system is modeled as an Erdös and Rényi random network. Hence p defines the average degree of interconnectedness within the network and the degree distribution follows a binomial. Corroborated by empirical evidence, a number of recent works have explored the role of heterogeneity along several dimensions. For example, Pegoraro (2012) tested how alternative network topologies (such as small-world or scale-free networks) affect aggregate resilience. Amini et al. (2011) and Sachs (2010) assess the role of heterogeneity in interbank exposures, Caccioli et al. (2012) study the role of heterogeneity in the number of in-coming and out-going links, Iori et al. (2006) assess the role of heterogeneity in bank size (deposits) and investment opportunities. Battiston et al. (2012b) show what happens when heterogeneity is introduced with respect to the financial robustness of each bank. We reckon that the homogenous case represents a worth-studying benchmark but we acknowledge the importance of this issue. Heterogeneity along selected dimensions surely will be added in future works.

[5]To avoid confusion, let us call aggregate interbank liabilities within the banking system $B = \sum_{i=1}^{n} B_i$ and total interbank liabilities (of a single bank i) $B_i = \sum_{j=1}^{n} B_{ij}$

Table 2: Balance Sheet Identities

$A_i = \alpha B_i$
$NW_i = \beta[A_i + L_i]$
$D_i = A_i + L_i - NW_i - B_i$

interconnectedness levels p, it could happen that the row i of the liability matrix X^l only contains zeros. This could create a zero-item balance sheet or a non-active bank. In order to avoid that, we force at least one non-zero element in each row i of the adjacency matrix, regardless of the degree of interconnectedness. Second, the amount of deposits required to net out assets and liabilities could be a negative number. This does not make sense in economic terms, and, for such reason, whenever D_i turns out negative, we increase the amount of external assets A_i enough to make $D_i = 0$. We recompute NW_i given the new value of A_i. Finally, we make sure that liabilities and assets do match. Because NW_i has been updated now, it could be that liabilities are greater than assets. Shall this happens, we further increase A_i to fill the gap. With this procedure we make sure that all elements of the asset structure are at least non-negative. It is possible that the *ex-post* values for α and β are not exactly the ones we set *ex-ante* but the deviations from it are negligible.

Third, we allow for heterogeneity in single-loan size but we adjust the liability matrix to keep constant the total value of interbank liabilities across all banks, so that bank size is (almost) homogenous in the network. More specifically, we divide each cell X^l_{ij} by the number of active loans taken by each bank i, so that the value of total interbank liability is set exogenously (say $B_i = 10$ units) and $B_{ij} = B_i / \sum_{j=1}^{n} M_{ij}$, where M is the adjacency matrix consistent with the liability matrix X^l. This is the similar to the procedure used in Gai and Kapadia (2010). For example, if bank i only has one connection, then it will borrow 10 units from the creditor bank. If bank i has 2 connections, then it will borrow 5 from each creditor bank and so on. In this way we make sure that $B_i = \sum_{j=1}^{n} B_{ij} = 10 = \sum_{j=1}^{n} X^l_{ij}$ regardless the level of interconnectedness p or realization of links for any specific bank. This normalization of X^l allows us to keep the aggregate value of total assets/borrowing/net-worth constant as we increase interconnectedness.

3.2 Shock-Propagation and Contagion Dynamics

In this paper, we only focus on direct contagion that works through interbank exposures.[6]

We introduce an exogenous shock $S_i(1)$ that wipes out all the external assets of bank i at time 1 and we let the system adjust to it. A distressed mortgage could be interpreted as a shock to external assets. Alternatively, this collapse could be due to fraud. A third possibility would be that of a bank suffering a run on its deposits which translates into a shock to its liquid assets. This latter case is consistent with an exogenous shock to the bank's deposits with external assets adjusting consequently to accommodate the loss. While we do not explicitly model this third type of shock, one could make room for it rather easily.

Is important to note that the size of exogenous shock relative to aggregate net-worth $S_i(1)/\sum_i NW_i$ is independent of p, whereas $S_i/\sum_i \sum_j A_{ij}$ falls with increasing degrees of interconnectedness. In order to check what happens when we increase the degree of interconnectedness, the default cascades are best comparable if the size of the shock relative to aggregate net-worth does not change. This ratio gives us a measure of the resilience of the

[6] The literature has examined different kinds of direct and indirect contagion mechanisms. Upper (2011) provides a comprehensive survey on the possible channels through which contagion can occur.

system (net of network effects) that does not depend on the degree of interconnectedness.

The failure condition is given by $NW_i(t) - S_i(t) \leqslant 0$: whenever a bank i takes a hit ($S_i(t)$) to its assets , it fails if it does not have enough capital ($NW_i(t)$) to absorb the shock.

The shock is computed as $S_i = \gamma A_i$ with $\gamma = 1$. We only hit one bank at a time and we let the system adjust to it . We now introduce the two mechanisms that govern the post-default management of the bank and the propagation of losses throughout the network.

- ***Bail-in*** :

  The bail-in mechanism works as follows. Distress occurs whenever a bank is buffeted by a shock and its total liabilities become greater than its assets total, with the consequence that the bank's net-worth turns negative. This triggers the bail-in power and enables the authority to force a recapitalization of the bank at the expense of the creditors. External debt is converted into equity up until a minimum viability threshold is reached. The main consequence of this action is that the troubled bank is not forced into compulsory liquidation. On the contrary, its basic operation are preserved and the institution remains active in the network. On top of this recapitalization, one can think that the regulator guarantees their liabilities at the hold-to-maturity value. Let us stress that this shall not be interpreted as a bail-out because it does not call for any government-funded money injection in the banking system. As previously discussed, the core-objective of bail-in is to provide a mean of resolving bank without closure.[7] Our modeling strategy is consistent with preserving this idea and does not capture the complexity naturally embedded in real bail-in interventions. More specifically, we abstract from issues related to the selection of debt instruments subject to bail-in because we only have one class of non-core liabilities (i.e. interbank liabilities). We also make the simplifying assumption that the viability threshold is set to zero. In real worlds, one would need to distinguish between wholesale funding, overnight transactions, short-term interbank loans, OTC derivatives and secured and unsecured long-term debt, repos etc. and provide a pecking order for bail-in. In addition, the viability threshold is likely to be set above zero. To a large extent, these are policy decisions and depends on institutional factors that at this stage we shall not bring into the picture. Whilst we acknowledge that these aspects are important, the uncertainty regarding the regulatory framework would force us to speculate on possible routes. In addition, a fully fledged bail-in model with accurately defined balance sheets would hardly be comparable with the simplified set-up of the alternative resolution procedure, i.e. the liquidation model. Let us also stress that the introduction of these aspects would improve the effectiveness of bail-in (i.e. think of a positive viability threshold) so that our result can be taken as an upper bound for the contagion profile under bail-in.

  The dynamic adjustment works as follows: if $NW_i - S_i < 0$ then bank i will not be able to honor part of its liabilities and will be declared insolvent. At each round, each bank holding interbank assets against one or more failing institutions will be required to bail-in and some (or all) of their interbank assets will be written off. The value of their interbank assets evolves according to the following rule:

$$L_{ji}(t+1) = [1 - \theta_i(t)]L_{ji}(t) \tag{1}$$

[7]It is clear that the appeal of the closure option increases with the efficiency of the liquidation procedure. Disordered liquidation may be very costly and long and this may be so particularly in countries that do not have a bank-specific bankruptcy code. For example, Italy, the UK, the US and Norway have special procedures for financial institutions whereas in other countries the bankruptcy code is the same as that of non-financial firms.

where $L_{ji}(t)$ is the value of the outstanding loan at time t made from bank j to bank i and θ is loss-given-default.[8]

The total value of interbank assets for each bank j at each time-round t is simply computed as:

$$L_j(t) = \sum_{i \neq j} L_{ji}(t) \tag{2}$$

and:

$$1 - \theta_i(t) = \begin{cases} 1 - \frac{(S_i(t) - NW_i(t))}{B_i(t)} & \text{if } B_i(t) - [S_i(t) - NW_i(t)] > 0 \\ 1 & \text{if } B_i(t) - [S_i(t) - NW_i(t)] < 0 \end{cases} \tag{3}$$

$1 - \theta_i(t)$ represents the share of non-distressed loans made to bank i at each time-round during the contagion process. Suppose that $\theta_i(t) = 0.7$ This means that each creditor will then lose 70% of the value of its claim against bank i. $1 - \theta_i(t)$ can loosely be interpreted as the recovery rate at time t for the banks connected to the failing bank i.

Let us stress that, as discussed in Upper (2011), the vast majority of papers in the area are based on the sequential algorithm proposed by Furfine (2003) in which the recovery rate is exogenously given. We make an explicit effort to go beyond this restrictive assumption. Indeed, the upside of our mechanism is that it provides a fully endogenous bank-specific $\theta_i(t)$ (see eq. 4).

In our simulations, each defaulted bank also fuels shocks to other banks in the post-default rounds, provided that its interbank liabilities are not entirely dried up yet. Even in this case, though, the contagion can destroy some of its interbank assets in post-default time-rounds, and, as such, it still affects the amount of dislocated assets in the system and the loss ultimately borne by depositors.

The importance of higher-order losses has been discussed by Upper (2011). Our mechanism of allocation of losses embeds them within an explicit bail-in framework in which the diffusion of contagion is though not instantaneous as in Eisenberg and Noe (2001).

As an example, one can look at Table 3 to appreciate how this assumption may affect the severity of contagion dynamics. With higher-order losses, bank c does indeed fail at time t+2 and that occurs because bank b (failed at time t) is kept in the system and contributes to spread higher-order losses in post-default rounds.

We now introduce the dynamic adjustment consistent with the resolution with bank liquidation.

- ***Liquidation***

  Whenever there is a loss in excess of the bank's equity, the bank fails and it is immediately wound up. As explained in the previous section, this process entails that all its assets are sold and that includes interbank assets.[9] The money raised with the sale of assets is then distributed to creditors with priority given to depositors. Within each given category of

[8] Let us assume that the exogenous shock is given to bank i at time $t = 1$. This means that $L_{ji}(1) = X^l_{ij}$ $\forall$ i, j. The rule of motion as in equation 1 allows us to fill in the matrix of non-distressed loans ($L_{ji}(t)$) for $t > 1$) at each time-round during the contagion process.

[9] We are aware that our framework is one of partial equilibrium. At this stage, we follow the existing literature and do not take into account the demand side of the market. We assume market clearing (infinitely elastic demand) and we do not model who is actually buying these assets. Both of these aspects clearly deserve a deeper investigation and may have important implication. A proper assessment of these issues is far beyond the scope of this paper and we leave it for further research.

Table 3: Contagion Dynamics

Time-Rounds	Contagion	Losses-given-default	Default
t	i $\Longrightarrow$ j i $\Longrightarrow$ b	$\theta_i(t)L_{j,i}(t)$ $\theta_i(t)L_{b,i}(t)$	$\theta_i(t)L_{j,i}(t) > NW_j(t) \Longrightarrow$ j=Default(t) $\theta_i(t)L_{b,i}(t) > NW_b(t) \Longrightarrow$ b=Default(t)
$t+1$	j,b $\Longrightarrow$ e	$\theta_b(t+1)L_{e,b}(t+1) + \theta_j(t+1)L_{e,j}(t+1)$	$\theta_b(t+1)L_{e,b}(t+1) + \theta_j(t+1)L_{e,j}(t+1) > NW_e(t+1)$ $\Longrightarrow e = Default(t+1)$
	b $\Longrightarrow$ c	$\theta_b(t+1)L_{c,b}(t+1)$	$\theta_b(t+1)L_{c,b}(t+1) < NW_c(t+1)$ $\Longrightarrow c \neq Default(t+1)$
	j $\Longrightarrow$ b	$\theta_j(t+1)L_{b,j}(t+1)$	$\theta_j(t+1)L_{b,j}(t+1) + \theta_i(t)L_{b,i}(t+1) > NW_b(t+1)$ $\Longrightarrow b = Default(t+1)$
$t+2$	b $\Longrightarrow$ c	$\theta_b(t+2)L_{c,b}(t+2)$	$\theta_b(t+2)L_{c,b}(t+2) > NW_c(t+2)$ $\Longrightarrow c = Default(t+2)$

creditors, equal seniority is assumed for all agents. This assumption implies that residual losses are equally distributed in percentage terms among creditors of the same type. We first assume that it is able to sell at face-value its external assets and successfully call in its interbank loans. This latter operation triggers a funding shock to neighbor banks that were granted a credit line from the failed bank. Their loans are not rolled over and they have to pay them back using their liquid assets. Shall they not have enough liquidity to cope with this unforseen shock, they will also fail. The minimum amount of liquid assets that each bank is required to hold is set by the central bank and in our model this is controlled by the policy parameter δ. δ defines the fraction of external assets (A_i) that are to be kept as liquid assets ($A_i^l = \delta A_i$).[10] It is clear that the bank j will experience an illiquidity-driven failure whenever $A_j^l < L_{ij}^c$, where L_{ij}^c is the amount of interbank assets called back in or not rolled over to bank j by the defaulting neighbor bank i.

Let us note again that the failed banks, once their assets are sold and their creditors are compensated, disappear from the network and can no longer contribute to spread contagion in post-default rounds. In other words, higher-order losses are ruled out. θ is again computed endogenously and let us point out that here the residual shock passed on to creditors depends on the realized value of sold assets, set by the fire-sale parameter ϕ. If a bank i defaults, its creditor banks will recover a fraction $1-\theta$ defined as follows:

$$1-\theta_i(t) = \begin{cases} \frac{\phi A_i(t)+L_i(t)-D_i(t)}{B_i(t)} & \text{if } 0 \leq \frac{\phi A_i(t)+L_i(t)-NW_i(t)-D_i(t)}{B_i(t)} \leq 1 \\ 0 & \text{if } \frac{\phi A_i(t)+L_i(t)-NW_i(t)-D_i(t)}{B_i(t)} < 0 \end{cases} \tag{4}$$

3.3 Parameters Calibration

Table 4 displays all the relevant parameters of the model, their description and range of variation. β is assumed to be homogenous across all banks. One can think of β as a policy parameter that specifies how much capital banks are required to hold, and we assume that all banks stick to this minimum. Of course, this is a simplifying assumption and, in real systems, we observe some degree of heterogeneity that can be easily embedded in the model without altering in any fundamental way the results of our paper. For the objective of this analysis, it is more interesting to vary the aggregate level of capital in the system and observe how contagion dynamics change with it.

Let us stress that β is defined as a non-risk-weighted ratio and it corresponds to a leverage ratio. Gai and Kapadia (2010) suggest 4 percent as a reasonable estimate from the 2005 data

[10]Liquid assets typically include cash and cash equivalents such as treasury bills, central bank reserves, etc.

extrapolated from published accounts of large international financial institutions. More importantly, the Basel Committee on Banking Supervision has announced that banks will be ask do disclose their non-risk based leverage levels from the beginning of 2015 and will have to comply with the new 3 percent minimum from January 1, 2018.[11] Hence we set 3 percent as our benchmark. The considered range of variation (1-7 percent) is broadly in line with the dispersion empirically observed for systemically important institutions.[12]

For the purpose of this study, also α is kept constant for all banks. In such a way, with this parameter we can control the aggregate size of the interbank market. Setting $\alpha = 5$ would yield a size of the interbank market as large as 16 percent of total assets, as it currently is in Italy (see Manna and Iazzetta (2009)). Upper (2011) shows that in some countries there is a great deal of heterogeneity in the α. For instance, 25 percent of the UK banks have interbank assets that account for more than 40 percent of their total assets. Swiss banks have a even larger share on interbank assets. For these countries, $\alpha = 2$ is not an unreasonable number.

The magnitude of the shock is obviously an arbitrary choice. Nonetheless, a term of comparison may be useful to avail a sense of what a reasonable systemic shock may look like. Manna and Schiavone (2012) suggest that bad debts amount to about 1 percent of the total assets of the system in Italy. In their simulation, they use a shock ranging from 1 to 4 percent of aggregate assets of the system. Here the system-wide value of assets amounts to 1500 units and each bank has a size of about 60 units. This means that we are exogenously wiping out 3.3 percent of total assets. 1 percent could be regarded as natural rate of bad loans that the system is, under normal circumstances capable, of absorbing without treats for the viability of the system. A larger shock such as 3 percent or more could pose a non-negligible systemic risk.

Let us also point out that we chose a small network of 25 banks. This is of course an arbitrary choice that can be justified on two grounds: first, Haldane (2013) shows that most modern banking systems are characterized by degree of concentration that has increased for the last 20 years and we now have that the top 3 banks account for a market share of 40 (US), 60 (Switzerland), 70 (Germany) up to 80 percent for the UK. One could legitimately argue that the first 25 banks in virtually any developed country would be a sufficient number to almost fully characterize the market. Manna and Iazzetta (2009) report that the top 20 banking groups in Italy account for 80 percent of the market and the top 5 groups have a share higher than 55 percent in 2007. Gai et al. (2011) show the network of large exposure between UK banks in 2008 and their network comprises 24 banks. Second, that is a size that allows us to model a systemic shock with a single seed. In fact, we exogenously fail 1 out of 25 banks, which amounts to 4 percent of the network and again this could be regarded as a systemic shock. The analysis in larger networks would require multiple-seeds and that is making the analysis more complicated without necessarily improving our understanding of the topic analyzed in this paper. Previous results put forward by Gleeson et al. (2013) suggest that this would yield remarkably similar results.[13]

We assess contagion dynamics with and without fire-sales, respectively obtained with $\phi = 0.7$ and $\phi = 1$. Historical records on recovery rate of sold assets in past banking crises provides us with little information in this regard. James (1991) suggests that the losses in the mid-1980s amounted to 30 percent on average. Hence, we set partial recovery equal to 70 percent. Let us stress that we do not model the indirect negative price externality possibly associated with

[11] Admati and Hellwig (2013) convincingly illustrate the dangers associated with the excessive reliance on risk-weighted ratios and explain why the banking supervisory authorities are rightly starting to introduce non-weighted measure of leverage.

[12] See, for example, the FDIC recent release on bank capital in second quarter of 2013 available at $http://www.fdic.gov/about/learn/board/hoenig/capitalizationratios.pdf$.

[13] One important caveat is that a meaningful comparison is only possible provided that ceteris paribus the different networks have the same average degree and the small-seed condition applies as suggested by Watts (2002).

fire-sales of publicly-traded assets (see Nier et al. (2007), Gai and Kapadia (2010)). As shown in previous works, the inclusion of this type of dynamic was proven to have a far-reaching shock-amplifying effect on default cascades.

The severity of contagion is evaluated under two different exogenous liquidity requirements: $\delta = 0.05$ (as benchmark) and $\delta = 0.1$. Gai et al. (2011) calibrate liquid assets as 2 percent of total assets. We define our liquidity ratio with respect to external assets and, for this reason, we adjust upward our parameter. Let us also note that our range of variation is consistent with the empirical evidence. Acharya et al. (2011) report the average liquidity buffer (with respect to total assets) of U.S commercial banks. Liquidity has constantly been falling from the early 1980s to right before the outbreak of the recent 2008-09 turmoil, starting from an initial 10 percent to 3-4 percent in September 2008. Liquidity hoarding contributed to have cash reserves skyrocketing to 8 percent at the beginning of 2009. As it will be shown, under some configuration of the network even a 10 percent threshold is not high enough to secure the system from systemic collapse.

Table 4: Description of Parameters

Parameters	Description	Benchmark Value	Range of Variation
n	Number of Nodes (Banks)	25	-
p	Degree of Interconnectedness	-	0.01-0.95
α	External Assets to Interbank Assets Ratio	5	2-5
β	Leverage Ratio	0.03	0.01-0.07
γ	Shock relative to the Ext. Assets of one bank	1	
θ	Loss Given Default	Endogenous	
ϕ	Fire-Sale Parameter	1	0.7-1
δ	Liquidity requirements (w.r.t. Ext. Assets)	0.05	0.05-$1/\alpha$

4 Simulation Results

Figures 1 to 4 illustrate the key results of our paper. Each panel reports a set of systemic default profiles - defined as the average over 100 Monte Carlo simulations of the aggregate default rate measured at the point a default cascade triggered by an idiosyncratic shock stops - as a function of the interbank connectedness. The first one of the seven profiles shown in each figure has been obtained under the bail-in resolution mechanism (black solid line), while the remaining ones refer to the liquidation rule for different values of the parameters tuning the liquidity ratio requirement (δ) and the recovery rate (ϕ), respectively.

The complex interaction of capital and liquidity requirements, interbank exposures and resolution mechanisms generates a rich variety of systemic behaviors. In particular, one can immediately appreciate how default profiles change significantly as we gradually move from a largely undercapitalized system with a shallow interbank market (top panel of Figure 1) to a well-capitalized system with a deep interbank market (bottom panel of Figure 4).

As the weight of non-core on total liabilities is kept constant, an increase in interbank connectedness generates an inverted U-shaped (or an M-shaped) graph - a well-known result in the literature, as recalled above - with the exception of the bottom panel of Figure 1, representing the case of a largely undercapitalized banking system ($\beta = 0.01$) with a deep interbank market ($\alpha = 2$). This latter is in fact the only instance where higher-order losses are quantitatively important to the point of dominating the disruption brought about by first-order funding shocks. Whilst banks lack adequate net-worth buffers to face negative external contingencies, a large chunk of their assets and liabilities (i.e. the interbank ones) are exposed to contagion spirals. In this context, the threshold beyond which risk-sharing effects more than offsets risk-spreading ones does not exist, with the consequence that the system never attains a point where increasing the level of connectedness can contribute to increase its resilience. In all other cases, a higher capital requirement contributes to strengthen the shock-absorbing capacity of interbank linkages for any value of the fraction of interbank exposures over total assets, as signaled by the correspondent reduction of the connectedness threshold above which the probability of contagion goes to zero. Furthermore, a pairwise comparison of the two panels forming each one of Figures 2-4 shows that, for any given leverage ratio at the 3% level or higher, an increase in the percentage of interbank assets comes with an intensification of contagion risks, given that the tipping point beyond which an extension of borrowing/lending linkages exert a risk-sharing beneficial effect forcing to zero the probability of contagion is lower for a higher value of the parameter.

More interesting for our purposes is what happens as we compare the impact on the default profiles of the two resolution mechanisms we are dealing with. One can immediately appreciate that the black line representing the bail-in solution lies below all the other profiles in every panels, but in the lower one of Figure 1. In this latter case, in fact, the higher-order losses that defaulted institutions spread out in post-shock rounds as long as they are preserved as a going concern have a stronger systemic impact than the funding shocks associated to an immediate close down of banks via a bankruptcy procedure. In all other instances, we observe that contagion dynamics fueled by both insolvency and illiquidity-driven defaults are stronger than those one would obtain under the bail-in mechanism. The benefit of a bail-in is even stronger when there is the concrete danger of ending up in a fire-sale spiral. This case is captured by a calibration of the fire-sale parameter to $\phi = 0.7$, a situation that is displayed in each plot by means of dashed lines. As one can see, the liquidation rule becomes obviously more costly with fire-sales not only for the single bank in distress but also for the system as a whole, given that default avalanches propagate faster and are noticeably more disruptive.

To a large extent, the contagion profile associated with a bail-in procedure dominates those derived by forcing the liquidation of distressed banks because, in the latter case, the counterparty risk externality is not tamed with adequate counter-measures aimed at containing the contagion. The standard way to deal with such an externality consists in applying a Pigovian tax to equalize the private and social costs associated to a systemic liquidity shock. As recognized by Perotti and Suarez (2011), any quantity-based liquidity requirement works as a de facto tax as well, with a levy that depends on the spread between funding and lending interest rates. Since in this case levies are endogenously defined by the interaction of a predetermined taxable income (i.e., the liquidity ratio settled by the regulatory authority) and the variable price of liquidity, however, a regulation based on quantity limits tends to be procyclical and secures a lower flexibility if compared to a time-varying Pigovian tax rate directly controlled by the regulator.

An alternative solution is that of allowing the liquidity taxable income to adjust endogenously, so that each bank is forced to internalize its contribution to system-wide costs on an automatic base. The Liquidity Coverage Ratio (LCR) introduced by the Basel III agreement - requiring that the ratio between the buffer of high quality liquid assets and the expected net cash outflow over the subsequent 30 calendar days under a stress scenario is equal to or higher than 1 - is consistent with this approach (Basel Committee on Banking Supervision (2013)).

Given the research question motivating this paper, in our model this issue is related to an assessment of whether it is possible to design an adjustment rule that can make the choice between the bail-in and the liquidation rules an unbiased one, in that the illiquidity-driven transmission mechanism associated to a cascade of withdrawals of interbank exposures can be offset. If the use of a prudential requirement ex ante is able make the choice of the resolution rule neutral from a systemic financial stability viewpoint ex post, in fact, the regulator gains one degree of freedom in deciding which approach should be followed in the case a systemic crises occurs, being able to base his decisions for example on political or employment concerns.

How should the regulator set liquidity requirements in order to absorb the liquidity externality arising when distressed banks go bankrupt? The contagion profiles consistent with different levels of liquidity requirements shown in each panel allow us to quantify the cost of the negative financial externality that arises with illiquidity-driven defaults, thus providing an answer to this question. To fix ideas, as we compare the black line (bail-in) with the light blue line (liquidity mechanism with $\delta = 0.05$), we observe that imposing a liquidity buffer of 5% of total assets is not enough to secure financial robustness. In fact, in this case default profiles are always much higher than what one would get with a bail-in mechanism, while the area between the two profiles can be interpreted as a measure of the systemic cost generated by the liquidity externality. By extending our analysis to different scenarios, we also observe that the required level of the liquidity buffer capable to tame the probability of contagion crucially depends on interbank exposures, so that a one-size-fits-all regulatory requirement independent of the deepness characterizing the financial connectedness between institutions cannot be applied. In particular, it turns out that the two resolution mechanisms virtually yield the same contagion profile when the liquidity buffer obeys to the principle $\delta = 1/\alpha$, that is when banks match one unit of non-core liabilities with one unit of liquid assets.

Several additional remarks are in order. First, it turns out that the bail-in mechanism enhances the robustness of the system if it is relatively low connected, but it brings little improvements in a highly interconnected network. In this case, a thick structure of claims favors shock-absorbing feedbacks over the risk-spreading ones, so that the dumping effect overrides funding shocks as well. On the contrary, a sparse network structure helps shock-amplifying dynamics to prevail and funding shocks to further exacerbate contagion. Furthermore, funding shocks play a minor role in shallow interbank markets, but they become a powerful source of instability in deeper markets.

Second, in a scenario characterized by a shallow interbank market and full recovery, setting a wrong - i.e., too low - liquidity requirement does not dramatically destabilize the system. For example, setting a 10% liquidity requirement in a network with $\alpha = 5$ (see the top panel in Figures 2, 3 and 4) does a satisfactory job even though this value is fairly below the optimal prescription $\delta = 1/\alpha$.

Third, the interaction of low liquidity requirements and a low recovery rate on fire-sold assets can destabilize even a well-capitalized system provided that the connectedness is low, as shown in the bottom panel of Figure 4.

Furthermore, as one can gauge from a visual inspection of Figure 1(top panel), the dashed lines consistent with different liquidity requirements are indistinguishable. In other words, increasing liquidity requirements may not help much when a premature liquidation of illiquid assets causes a recovery rate lower than face value. Under these circumstances, strengthening capital is a better regulatory response, especially in medium-connected systems, as it should be clear from a comparison of the contagion profiles under fire-sales shown in Figure 1 (top panel with capital 1%) with those displayed in Figure 2 (top panel with capital 3 %). Finally, our simulations show that the higher the net-worth endowment, the more effective liquidity requirements become in containing losses fueled by inefficient fire-sales. At a glance, the dashed lines show that the effect of tighter liquidity is much stronger in a capitalized system depicted in Figure 4 (top panel) than what it would be in a undercapitalized network as in Figure 1 (top panel).

5 Final Remarks

The present analysis provides a framework that allows us to quantify the cost of the negative financial externality that arises with illiquidity-driven defaults. Our results may provide useful guidance for the regulation of the banking system in light of the set of rules put forward by the Basel III agreement. The recently introduced liquidity coverage ratio (LCR) is calibrated to enable a bank to successfully withstand a net outflow of funds for a prolonged period of 30 days. This choice complies with a micro prudential rationale that aims at minimizing the chances of a illiquidity-driven collapse of one single bank. In this paper we provide an additional macro-prudential criterion to judge the adequacy of the this new requirement. Our analysis suggests that the proposed reforms can be further improved by having liquidity requirements directly tied down to the exposure on the interbank market. This acts as a Pigovian tax and forces banks to internalize the cost of unforseen liquidity shocks that would otherwise amplify contagion dynamics. Our results show that the negative financial externality induced by illiquidity-driven default is completely internalized and contagion dynamics are fully comparable with those that one would obtain with a bail-in policy. Our findings entail a kind of neutrality result, in that a regulator doomed to choose which one between the two resolution measures has to be implemented should base his decision not on the financial fragility effects it could have which would in fact be identical but on considerations regarding their relative technical feasibility or political viability.

We have also showed that severe underpricing of fire-sold assets may render higher liquidity requirements ineffective in an undercapitalized system. This is so because the effect of fire-sales is so disruptive that contagion dynamics are almost entirely governed by insolvency-driven defaults. If this is the case, the response is higher capital requirements. On the other hand, we observe that setting a wrong (too low) liquidity requirement in a fire-sale-free network with shallow interbank market, does not dramatically destabilize the system. A deeper interbank market weakens the system to a greater extent even with full recovery of assets. This does not necessarily imply that we advocate for a shrinkage of the interbank market as this would affect the provision of liquidity and the efficiency of fund allocation. It is nonetheless important to be aware of the possible trade-offs associated with the size of this market. Finally, the regulator should favor the formation of networks with interconnectedness levels in the desired range given the structure of the banking system, such that capital and liquidity requirements can be best effective.

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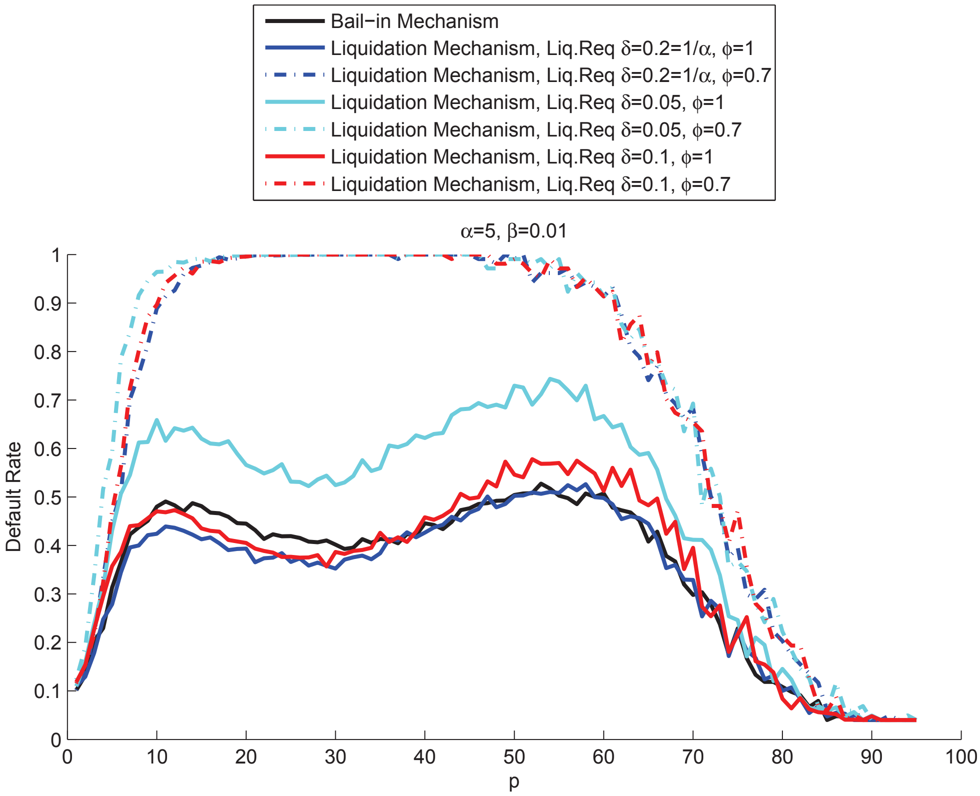
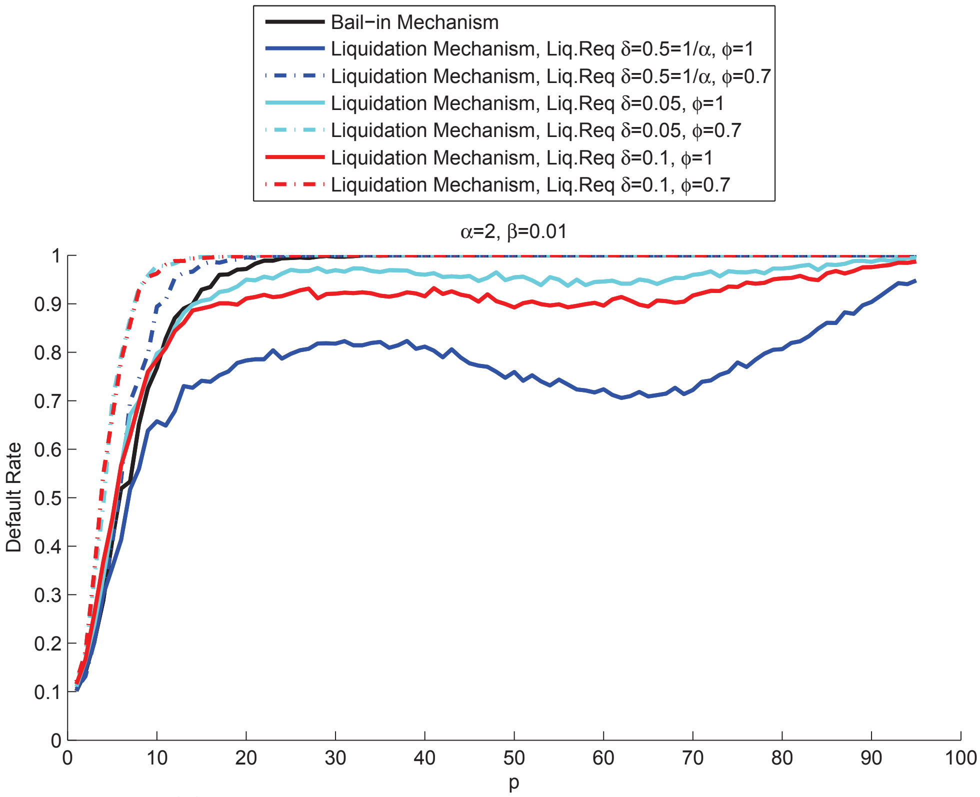
Figures

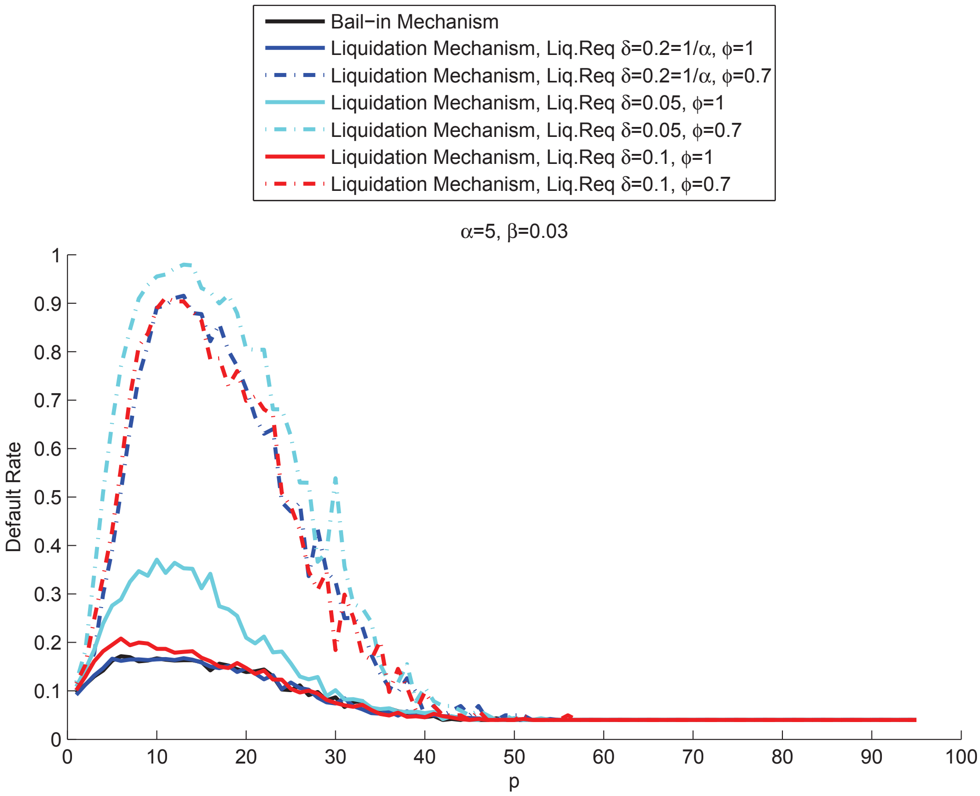


(a) Shallow Interbank Market - Undercapitalized System

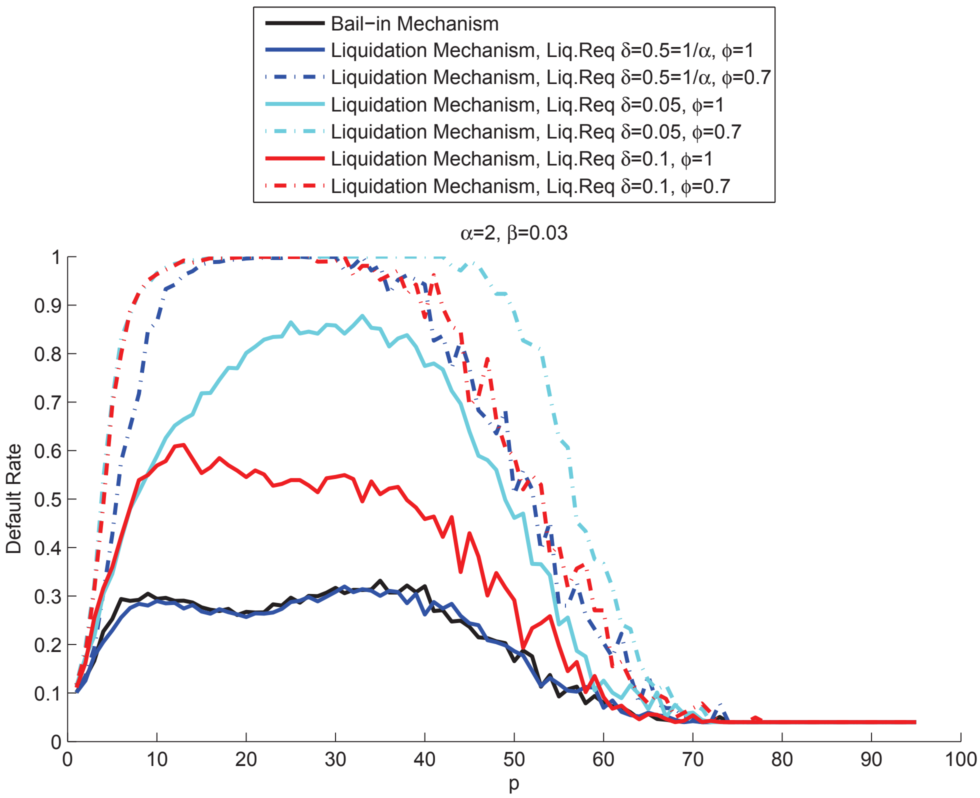


(b) Deep Interbank Market - Undercapitalized System

Figure 1: Monte Carlo Experiments

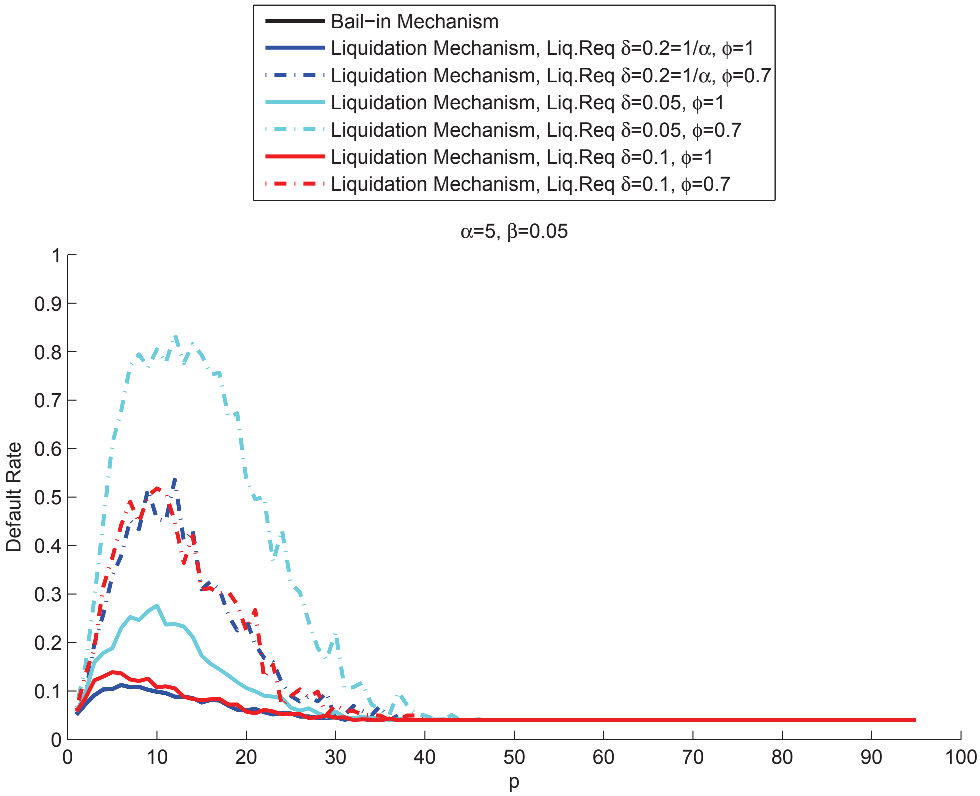


(a) Shallow Interbank Market - Weakly Capitalized System

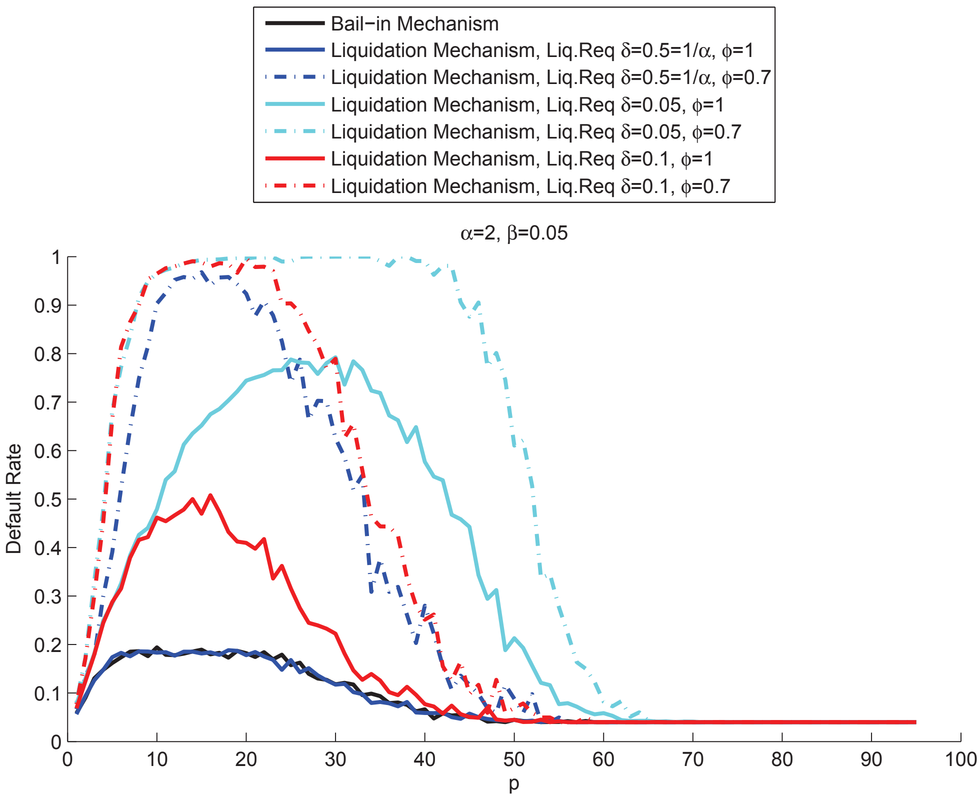


(b) Deep Interbank Market - Weakly Capitalized System

Figure 2: Monte Carlo Experiments

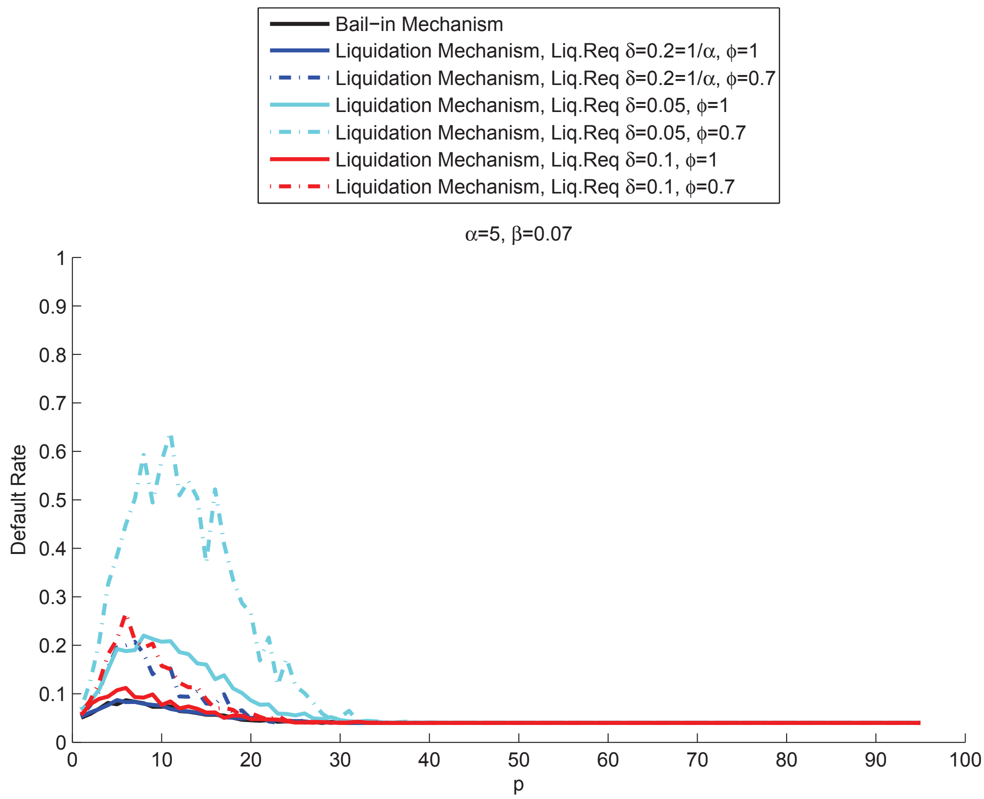


(a) Shallow Interbank Market - Medium-Capitalized System

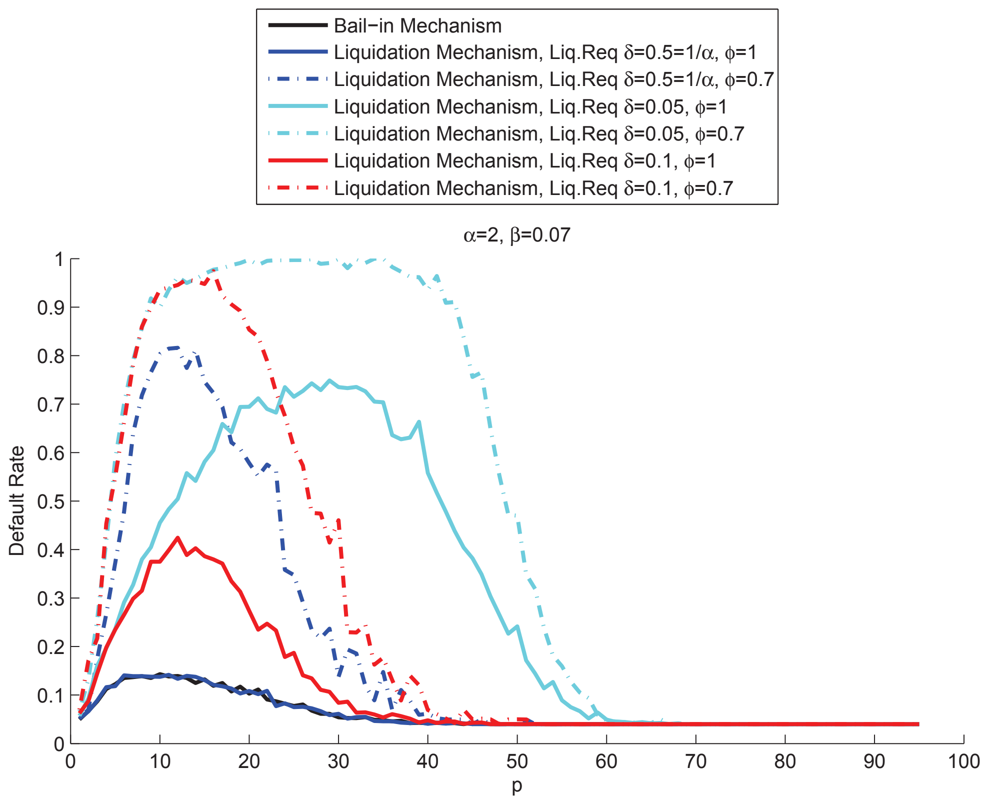


(b) Deep Interbank Market - Medium-Capitalized System

Figure 3: Monte Carlo Experiments



(a) Shallow Interbank Market - Highly-Capitalized System



(b) Deep Interbank Market - Highly-Capitalized System

Figure 4: Monte Carlo Experiments

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