Monetary Policy Implementation in an Interbank Network: Effects on Systemic Risk*

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Abstract

This paper makes a conceptual contribution to the effect of monetary policy on financial stability. We develop a microfounded network model with endogenous network formation to analyze the impact of central banks' monetary policy interventions on systemic risk. Banks choose their portfolio, including their borrowing and lending decisions on the interbank market, to maximize profit subject to regulatory constraints in an asset-liability framework. Systemic risk arises in the form of multiple bank defaults driven by common shock exposure on asset markets, direct contagion via the interbank market, and firesale spirals. The central bank injects or withdraws liquidity on the interbank markets to achieve its desired interest rate target. A tension arises between the beneficial effects of stabilized interest rates and increased loan volume and the detrimental effects of higher risk taking incentives. We find that central bank supply of liquidity quite generally increases systemic risk.

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1 Introduction

The question as to whether and how monetary policy can foster financial stability has always played a prominent role in the literature and it has become paramount after the recent global financial crisis.[1] In macro models this question has typically been answered by analyzing whether targeting financial variables in operational monetary policy rules can smooth the volatility of asset prices and other financial variables. But this modeling framework typically neglected important aspects of financial instability, namely the diffusion of risk through firesales spirals and direct interconnections within the banking system. These network features are crucial characteristics of the overnight interbank market, where monetary policy implementation takes place through the supply of liquidity and interest rate expectations.[2] Some authors[3] have been stressing the importance that the exact terms of the monetary policy implementation in markets that involve networks of banks is a crucial element in determining how its interventions can affect market liquidity as well as systemic risk, namely the cascading effects through which shocks to one bank are transmitted to other banks in the network (see, for example, Gauthier, Lehar, and Souissi [30] or Bluhm and Krahnen [31].). In this context important tensions emerge. Consider for instance the implementation of expansionary monetary policies. On the one side, increases in liquidity supply lubricate banks trading relationships and reduce the probability of liquidity shortages. On the other side, higher availability of short term liquidity might provide incentives to invest in risky assets, thereby increasing banks' risk appetite and risk taking. As in the face of negative shocks, banks might anticipate the willingness of the monetary authority to provide liquidity at discounted prices, risk taking effectively results from moral hazard triggered by an implicit monetary policy guarantee. The

[1] Stein [38].
[2] Friedman and Kuttner [20].
[3] See, for instance, Acharya, Portes, and Reid [1].

tension described suggests an effect on systemic risk to be an unintended consequence of monetary policy implementation. On the one side, increased liquidity allows banks to be resilient to adverse shocks. On the other side, higher risk taking carries an externality, increasing the likelihood of adverse shock transmission to the overall banking system as well as the real economy. In this paper we assess quantitatively the tension between those two forces to establish whether in a banking network, with empirically plausible calibrated values, monetary policy induces an overall increase or a decrease of systemic risk.

To this purpose we construct a dynamic network model with heterogenous and micro-founded banks, whose links emerge endogenously from the interaction of intermediaries' optimizing decisions and an iterative tâtonnement process which determines market prices endogenously. The financial system featured in our model consists of a network with a finite number of financial institutions which solve an optimal portfolio problem, taking into account liquidity and capital constraints. Banks hold different amounts of equity capital and differ for the returns on non-liquid assets due to different information and administrative costs. Such differences in returns gives rise to heterogenous optimal portfolio allocations of banks' assets and residual liabilities, hence to excess demand or supply of bank borrowing and lending. Links among banks are determined by lending and borrowing decisions that are cleared and settled in the interbank market. A crucial feature of our model is that the links in the adjacency matrix characterizing the network are not assigned randomly as in random network models but emerge endogenously from the combination of the banks' optimizing decisions.[4]

The central bank is introduced in the model as an additional agent who intervenes on the interbank market via supplying or demanding liquidity. It is characterized by a predetermined monetary policy goal, namely achieving

[4]Furthermore, dynamic adjustment in our model emerges as an intrinsic feature of the market adjustment even in absence of an initial shock impulse.

a given target interest rate, and the absence of a funding constraint (fiat money).

Systemic risk manifests in our model through cascades of bank defaults. Shocks to one bank can be transmitted to others through two channels: common exposure to risky assets and local network externalities. First, if banks invest in the same financial products, their balance sheets are correlated due to the multinomial nature of the shocks. Second, contagion takes place directly and indirectly as banks are interlinked through counterparty exposure. Indirect contagion effects manifest through fire-sales (pecuniary externalities). A negative shock in the value of non-liquid assets induces several banks to de-leverage in order to satisfy their regulatory requirements: this is a credit event that produces a fall in the market price and a cascade of losses in marked-to-market balance sheet of all other banks. Direct contagion takes place via the interbank market. If a debtor bank defaults on its liability, its creditor bank receives a negative shock, potentially leading to further contagion. The cascading sequences of defaults effectively constitute an endogenous risk propagation mechanism.

In our quantitative simulations we analyze the impact of central bank interventions on systemic risk for different values of institutional parameters characterizing the banking network. The parameter we focus our analysis on is banks' capital requirement. As a further analysis we also consider changes in banks' required liquidity ratios. Generally speaking we find that central bank interventions tend to increase overall systemic risk relative to the case in which the financial system reaches an equilibrium without any central bank intervention.

The themes addressed in this paper relate to different strands of the literature. First, the introduction of banking in a monetary policy context dates at least back to Bagehot [6] who stresses the lender-of-last-resort role of the central bank for banks' lending decisions. More recently, the interaction of banking and monetary policy has been approached from two directions, namely from the side of banks as lenders (emphasizing moral hazard), and from the side of banks as borrowers (emphasizing funding constraints). The first one is focussing on the borrower-lender relationship under asymmetric information in the spirit of Stiglitz and Weiss [39], as well as in the works of Bernanke and Gertler [8], Kyotaki and Moore [32], and Adrian and Shin [2].

The second approach builds on institutional rules of monetary policy, for instance the role of bank reserve requirements for monetary policy transmission, as in the work of Bernanke and Blinder [7]. A common feature of these models is that banks are reduced form in the sense that they do not optimize their net worth. A third strand of related literature focuses on the interactions between banks subject to monetary policy impulses, as in Ho and Saunders [27] and Hamilton [26] who analyze the money market focusing on the microstructure of the banking relationships. Bartolini, Bertola and Prati [12] propose a model of the interbank money market with an explicit role for central bank intervention and analyze the interaction of profit-maximizing banks with a central bank targeting interest rates at high-frequency. Using Italian data Angeloni and Prati [5] assess the role of liquidity for interest rate volatility in the interbank market during 1991-1992, a period in which there were significant monetary policy interventions in the money market.

Fourth, this paper is related to to the literature on interbank networks. Over the last decade network models have emerged as an alternative paradigm to analyze a variety of economic and social problems ranging from the formation of contacts and links in labour, financial and product markets to the formation and evolution of research networks.[5] An early analysis is carried out in the seminal article by Allen and Gale who [4] exploit network externalities as banks in their model hold cross-deposits whose connections expose

[5]See Jackson [29].

them to contagion. More recently, the financial crisis has conveyed increased attention toward models featuring pecuniary and network externalities and to the measurement of systemic risk. In the extant network-based literature the interbank network structure is exogenously given or randomly assigned (see, for example, Cifuentes, Ferrucci, and Shin [15] and Gai and Kappadia [22]). Georg [21] uses a dynamic multi-agent model of a banking system with a central bank to compare different interbank network structures and provides evidence that money-center networks are more stable than random networks and that the central bank stabilizes interbank markets in the short run only. A number of other papers have dealt with the analysis of systemic risk: among others see Lagunof and Schreft [33] and Billio, Getmansky, Lo and Pelizzon [13]. [6] The model used in our analysis is closely related to that of Cifuentes, Ferrucci, and Shin [15] and Bluhm and Krahnen [31], extending the extant framework for endogenous network formation based on banks' profit optimization. Notice that our model uses a centralized market mechanism[7] for price formation. The algorithm developed to analyze the tâtonnement process of our model follows the traditions of clearing mechanisms that rely on lattice theory, most notably Eisenberg and Noe [18] who however take the banks' asset and liability structure as given.

The rest of the paper is structured as follows. Section 2 describes the model, the equilibrium, the shock transmission, and the measure of systemic risk. Section 3 describes the numerical results and analyzes the policy designs. Section 4 concludes.

[6] An overview on methods to assess the danger of contagion in interbank markets is provided in Upper [41]. Other noticeable network-based analyses include, but are not limited to, Degryse and Nguyen [16], Elsinger, Lehar, and Summer [19], and Upper and Worms [40].

[7] See also Cifuentes, Ferucci and Shin [15] or Duffie and Zhu [17] for other centralized mechanisms.

2 The Model

The financial system is made up with a population of N banks andfmarkets' a central bank which offers or withdraws liquidity. Let $N \in \{1, ..., n\}$ represent a finite set of individual banks, each of whom is identified with a node of the network. We define ex-ante for this population a network $g \in \mathcal{G}$ as the set of links among heterogenous banks N, with $\mathcal{G}$ being the set of all possible networks. An arc or a link between two banks i and j is denoted by $g_{i,j}$ where $g_{i,j} \in \mathbb{R}$. Here $g_{i,j} \neq 0$ reflects the presence of a link (directed network), while $g_{i,j} = 0$ reflects the absence of it. Later on we shall specify the link $g_{i,j}$ as either borrowing or lending from bank i to bank j, therefore the real valued link could take either a positive or a negative value. A crucial aspect of our analysis lies in the fact that those cross investment positions (hence the network links) result endogenously from the banks' optimizing decision and the market's tâtonnement processes. An important dimension in the diffusion of risk concerns the number of direct links held by each bank: a loss of value in the balance sheet of bank i will affect immediately all banks directly connected with bank i. For this reason it is instructive to define $N^d(i; g) = \{k \in N \mid g_{i,k} \neq 0\}$ as the set of banks with whom bank i has a direct link in the network. The cardinality of this set is given by $\mu_i^d(g) = \left|N^d(i; g)\right|$, namely the number of banks with whom bank i is directly linked in the network g. The $n - square$ adjacency matrix $\mathbf{G}^{(t)}$ of the network g describes the connections which arise after (t) iterations of the tâtonnement process described further below in more detail. Given that our model features a directed weighted network, banks i and j are directly connected if $g_{ij} \neq 0$.

Our network features optimizing banks which undertake an optimal portfolio allocation by maximizing profits subject to liquidity and capital requirement constraints. Banks decide about the optimal amounts of liquid assets (cash), lending and borrowing in the interbank market, and non-liquid assets (banks' loan book, bonds or collateralized debt obligations). Network externalities materialize through the lending and borrowing taking place in the interbank market, while pecuniary externalities materialize since non-liquid assets are marked-to-market. Banks differ for their equity endowment and return on non-liquid asset investments, which result, after optimization has taken place, in heterogenous optimal portfolio allocations. The optimizing decision together with the dynamic adjustment taking place in asset and interbank markets determines the final portfolio allocations and the final borrowing and lending positions in the interbank market: the latter represent the entry of the adjacency matrix $\mathbf{G}$ characterizing the interbank network. The central bank in our model is a large bank which supplies or withdraws liquidity to achieve an interest rate target compatibly with market equilibrium.

The clearing mechanism in our model is achieved through a sequential tâtonnement process[8] that takes place first in the interbank market (for given price of non-liquid assets) and subsequently in the market for non-liquid assets (for given clearing price in the interbank market). Central Walrasian auctioneers (see also Cifuentes, Ferucci and Shin [15] or Duffie and Zhu [17]) receive individual demand and supply of interbank lending and adjust prices until the distance between aggregate demand and supply has converged to zero:[9] the price adjustment in each market is done in fictional time during which trade does not take place. Once a clearing price has been achieved, actual trade in the interbank market takes place according to the criterion of the *closest matching partner*: to put it simply, banks wishing to borrow are matched with banks wishing to lend the closest possible amount. This matching mechanism is compatible with pair-wise efficiency and is in line with actual practice. Once equilibrium, both in price and quantities,

[8] See Mas-Colell and Whinston [35], and Mas-Colell [34].

[9] The convex banks' optimization problem and an exponential aggregate supply guarantee that individual and aggregate excess demands behave according to Liapunov convergence.

has been achieved we can analyze the final network configuration. The latter can however change once the asset portfolio of one bank is subject to shocks to non-liquid assets: the shock may trigger a new round of tâtonnement adjustments which result in fire-sales of non-liquid assets for banks wishing to adjust their equity ratios and in possible cascading defaults for banks which are unable to repay interbank debts.

2.1 Banks' Optimization

A bank's balance sheet consists of the elements displayed on Table 1.

Assets	Liabilities
Cash (c)	Deposits (d)
Bank lendings (l)	Bank borrowings (b)
Non-liquid assets (e)	Equity (q)

Table 1: Banks' Balance Sheets

Banks hold deposits, d, and choose cash, c, investment in non-liquid assets, e, and the amount of borrowing, b, or lending, l. We use the index i to indicate each individual bank, and we use the index j to indicate the trading partner of each bank. Banks' solve a static optimization problem which is detailed as follows. Bank i's objective function is given by:

$$E(\pi^i) = l^i \cdot r^{rf} + \frac{r^i}{p} \cdot e^i - b^i \cdot r^{rf} \cdot \frac{1}{1 - \xi PD^i}, \tag{1}$$

where π denotes profit, $l^i = \sum_{j=1}^{N} l^{i,j}$ is bank i's lending vis-à-vis all counterparties, $b^i = \sum_{j=1}^{N} b^{i,j}$ is bank i lending vis-à-vis all counterparties, r^{rf}, is the risk-free interest rate on the interbank market which will later on be determined through the centralized tâtonnement process, e^i is bank's i holding of non-liquid assets, p is the market price of the non-liquid asset, later determined through the centralized tâtonnement process in the market for non-liquid assets, r^i is the return on non-liquid assets, which is bank specific and set exogenously according to a uniform distribution. Heterogeneity in assets returns is meant to capture the fact that banks have access to investment opportunities with different profitability: this generates heterogeneity in asset and portfolios' positions and justifies the desire for trade in both interbank and asset markets. Finally the parameter ξ is the loss-given-default ratio: only a fraction of the outstanding amount is paid back in case of the debtor's default. Two considerations are important. First, notice that while non-liquid assets are traded at a single centralized price, whose changes trigger fire sale externalities on banks' asset portfolios, the return on bank borrowing features two components, a central clearing price, r^{rf}, common to all banks and an additional risk premium, $\frac{1}{1-\xi PD^i}$, which is bank specific. The latter is determined based on equilibrium consistent expectations of individual banks' default probabilities, which are obtained through a least square iterative process, as detailed in section 3.2. This assumption captures the idea that bank borrowing typically features heterogenous prices linked to individual bank's health. Second, the profit function takes into account the fact that in every period a fraction of banks might default on repayment. The possibility of sequential default is also the reason for which the return on bank lending does not include the premium: each lending bank charges premia to different counterparties; ex-post however some counterparties default and the return on bank lending is set to satisfy arbitrage on risky assets. A detailed derivation of Equation 1 that takes into account this mechanism can be found in Appendix A.

Banks face a *liquidity constraint*, of the type envisaged in Basel III agreements, due to which they have to hold at least a percentage, α, of their deposits in cash:

$$c^i \geq \alpha \cdot d \tag{2}$$

where c^i is the bank's holding of cash and d is an exogenous amount of deposits. Furthermore, banks face a *capital requirement constraint*, as they must maintain an equity ratio, er^i, of at least γ:

$$er^i = \frac{c^i + p \cdot e^i + l^i - d^i - b^i}{\chi_1 \cdot p \cdot e^i + \chi_2 l^i} \geq \gamma + \tau \tag{3}$$

where χ_1 and χ_2 are risk weights assigned respectively to the two risky assets, namely non-liquid investment and bank lending. The parameter γ identifies the regulatory requirement, while the parameter τ reflects banks preference for an additional capital buffer beyond the regulatory requirement. The risk coefficients are set exogenously as part of the regulatory system. Realistically we assume that banks need to hold less capital for bank lending than for investments in non-liquid assets, i.e. $\chi_1 \succ \chi_2$. More details on the exact numbers chosen in simulations are given in Section 3.6.

If banks' equity ratio, er^i, is lower than the minimum capital requirement, γ, banks can reduce their exposure to bank lending (or to non-liquid assets): effectively this results in a reduction of the denominator of Equation 3, relatively to the numerator, until the required ratio is achieved. This implies for instance, as we shall see later on, that any change in the regulatory capital requirement, γ, will result in a change of the demand (or supply) of bank lending in the interbank market, hence in a change of the cross-exposure of the network. Following the same mechanism, changes in the regulatory levels of the risk weights parameter χ_1 and χ_2 will also trigger an adjustment in the interbank and non-liquid asset markets. The higher are those weights, the larger is the extent to which banks have to re-adjust their non-liquid asset and bank lending positions in order to satisfy the capital requirement.

Three further observations are worth noticing. First, note that liquid assets do not appear in the denominator of Equation 3 since banks do not have to hold capital for their liquid asset holdings. Second, similar to Cifuentes, Ferucci, and Shin [15], non-liquid assets are marked to market, which gives the potential for fire-sale spirals in the model: if the price of non-liquid assets falls due to fire-sales, the asset values of all banks investing in non-liquid assets falls. Third, banks face a *no-short sales constraint*:

$$e^i \geq 0. \tag{4}$$

The latter is needed for the problem to be well-behaved: this indeed rules out the possibility of negative prices for non-liquid assets.

Individual banks' constrained optimal solution to their profit function which determines their optimal asset and liability allocations is found via maximizing Equation 1 subject to constraints 2, 3, and 4, using linear programming techniques. We also add four further constraints which make sure the solution is feasible. Due to the linear nature of both the objective and the constraints in the portfolio optimization problem and according to the *Duality Theorem of Linear Programing* we can reformulate the maximization problem as a minimization problem for the i^{th} bank subject to smaller equal constraints. The new constrained minimization problem reads as follows:

$$min_{l^i,b^i,e^i,c^i} \quad -E(\pi^i) = -e^i \cdot \frac{r^i}{p} - l^i \cdot r^{rf} + b^i \cdot r^{rf} \cdot \frac{1}{1-\xi PD^i} \tag{5}$$

s.t.

$$-c^i \leq -\alpha \cdot d$$

$$-c^i - e^i(p(1-(\gamma+\tau)\chi_1)) - l^i(1-(\gamma+\tau)\chi_2) + b^i \leq -d^i$$

$$e^i \geq 0; c^i \geq 0; b^i \geq 0; l^i \geq 0; c^i + e^i p + bl^i - bb^i = d^i + e^i$$

The next section describes the sequential tâtonnement processes, the role of the central bank in our model, and the respective clearing mechanisms in the interbank and non-liquid asset markets.

2.2 Tâtonnement in the Interbank Market, Central Bank Intervention, and Clearing Mechanism

The equilibrium allocation on the interbank market is found in two steps. The first step consists of finding the market clearing interest rates as well as the aggregate supply and demand of interbank funds. The second step consist of finding the allocation of interbank funds supplied in equilibrium, which then determines the structure of interlinkages between lending and borrowing banks.

The market clearing rates $r^{rf}+r^{PD^i}$ are found via a discrete tâtonnement process as follows. Given a set of parameters,[10] including r^{rf} and r^{PD^i}, banks optimize their portfolio via minimizing Equation 1 subject to the set of regulatory constraints (Equations 2 to 4). Banks submit their optimal demand and supply of funds to an auctioneer, which then sums them up to obtain the aggregate excess demand or supply in the interbank market and to adjust the price towards a direction consistent with market clearing. The interbank centralized rate, r^{rf}, is increased if $F^{supply} < F^{demand}$ and decreased in the opposite case, where F^{supply} and F^{demand} are the overall amounts of funds supplied and demanded, respectively. The rates are adjusted in fictional time until equilibrium is achieved and then actual trade takes place.

The exact implementation of the tâtonnement process is as follows. At time zero, there are three reference points: an upper interest bound, $\overline{r}_0^{rf}$, a lower interest bound, $\underline{r}_0^{rf}$, and the actual risk-free rate, r_0^{rf}. It is assumed that $\underline{r}_0^{rf} \leq r_0^{rf} \leq \overline{r}_0^{rf}$. Given those bounds and banks' initial optimal portfolio allocation there might be excess demand or supply on the interbank market. To fix ideas let's assume that there is an excess supply of bank lending. In this case the lending rate adjusts downwards to re-equilibrate bank lending. The new lending rate is set to $r_1^{rf} = \frac{r_0^{rf}+\underline{r}^{rf}}{2}$ and the new upper bound is set to $\overline{r}_1^{rf} = r_0^{rf}$. Given the new lending rates, banks re-optimize their portfolio allocation, which then results in new bank lending positions. Gradually, the excess supply of bank lending is absorbed through

[10]This set of parameters includes specific values for all regulatory requirements, in particular for γ (capital requirement ratio), χ_1 and χ_2 (risk weights on interbank assets and non-liquid assets), α (the liquidity ratio requirement); and banks capital endowment, in particular d (amount of deposits bank start with), and e^i (banks equity endowment).

this sequential adjustment of the lending rate. The opposite adjustment takes place if demand for liquidity exceeds supply. The process converges when the interest rate adjustment is below a tolerance value ϖ.

Once equilibrium amounts of funds exchanged on the interbank market have been obtained, it remains to determine the actual allocation of funds across banks, namely the interlinkages in the interbank market. Notice that banks are indifferent among different counterparties as they charge different risk premia based on individual banks' default risk An efficient allocation is then achieved simply by identifying the *closest matching partners*. Closest matching partners are lender-creditor pairs of banks which, within a specified set, feature the smallest distance between funds demand and supply. Consider for instance the following example: at market clearing prices the system consists of 4 banks wishing to lend and 2 banks wishing to borrow. Upon ordering of the respective demand and supply vectors, we can immediately identify two matching partners: two banks that demand money and the two banks which provide the largest amounts of funds. For each of those matching partners, the amount given by the minimum between demand and supply is exchanged. Given these transactions, two banks have satisfied their desired fund allocation and therefore become inactive: the matching process continues by sorting demand and supply vectors for the remaining banks until all transactions have been concluded.[11]

Central banks intervene in the interbank market both as part of the normal activity of their operational system as well as for unconventional interventions. Both the New York Fed and the ECB achieve the target policy rate by supplying or withdrawing liquidity from the market as part of their normal operational procedures. In times of financial crises and following the disruption of trust in the interbank market as well as the ensuing liquidity hoarding, central banks around the globe have taken unconventional

[11] Alternative allocation mechanisms can be used such as, for example, maximizing the number of counterparties to further diversify risk.

measures also with direct borrowing and lending to individual banks.

The central bank is defined as the $n + 1^{th}$ bank, where $n = 15$. This bank will neither hold cash nor non-liquid assets, but will solely supply or demand liquid funds on the interbank market with the goal of achieving the desired interest rate target. We assume that the central bank has unlimited funds and thus cannot default.

Prior to any shock central bank interventions can be characterized as follows. If the target interest rate, r^{rf} is below the equilibrium interest rate on the interbank market,[12] the central bank supplies money until the target is achieved. It demands money in the opposite case. Following endogenous changes in the financial system structure (e.g. through supervisory intervention) the equilibrium interest rate will deviate from the central bank's target: in this case the central bank intervenes via supplying or drawing liquidity to or from the market until the interest rate on the interbank market is within an interval band around its desired rate (the bands are set to 100 basis points). Given the interest rate equilibrium value the bands of the intervention corridor are set to .5 percentages points.

Note that the equilibrium set up of a financial system outlined in this sub-section is obtained for given individual probabilities of default. However, the probabilities of default which banks have assumed in their portfolio optimization might differ from actual probabilities of default in the financial system which emerges. The next sub-section outlines how equilibrium probabilities of default are determined in our model.

2.2.1 Model Equilibrium Consistent Expectations of Default

As explained above, the rate charged for borrowing includes a premium to cover for expected default probabilities: to this purpose we formulate a

[12]This corresponds to the equilibrium interest rate obtained in absence of any central bank intervention. Note that other interest target setting mechanisms are possible. For example, if the model is extended with a real economy sector, the interest rate target could be set with the aim to stabilize economic activity.

process through which banks form expectations about cross-sectional probabilities of banks' default. Beyond the recovery rate, ξ, which we assume to be a common parameter across banks,[13] in our model bank equilibrium probabilities of default, PD^i, are derived endogenously via an iterative algorithm. First, a bank defaults when its liquidity and the proceeds from selling non-liquid assets are not sufficient for repaying its debts in the interbank market; if we define s_i as bank i sales of non-liquid assets, the default probability of bank i is defined as follows:

$$PD^i = prob\left\{er^i < \gamma | c^i < \alpha \cdot d\right\} \tag{6}$$

We assume that agents form beliefs relatively to each bank's default probability by learning over time from the equilibrium of the financial systems subject to repeated shocks. As agents learn, the adjacency matrix describing the system reaches a stable configuration compatible with the limiting distribution for the vector of the default probabilities. Hence the underlying assumptions is that banks' expectations are consistent with a long run equilibrium of the model. Note that all agents share the same beliefs, that is, banks probabilities of default are common knowledge.

In the iterative procedure default probabilities are computed as follows. Banks' default probabilities are initially set to zero. First, for a given set of model parameters, a financial system forms as outlined in the previous sub-section, based on banks' individual portfolio choices, the tâtonnement process, and the interbank market allocation. Second, this specific financial system is then exposed to a large number of shocks.[14] Third, bank i's conditional probability of default is computed as the fraction of defaults of that bank in all shock scenarios. By the law of large numbers this percentage

[13]Following Grunert and Weber [24] this parameter is set to 0.75.

[14]We set this number being 100. Each shock is drawn from a multivariate normal distribution. Mean and variance are set to two and four, respectively. Correlation is assumed to be zero. The moments of distribution are chosen so as to rule out large tail events.

can be used to approximate the probability of default of bank i. These updated probabilities are then used as guesses for the default probabilities in computing a new financial system, that is, the first step outlined above is repeated until the financial system converges.[15]

2.3 Tâtonnement in the Market for Non-Liquid Assets

In the model, the market price of the non-liquid asset is found via a continuous time tâtonnement process (see also Cifuentes, Ferucci and Shin [15]). Sales and purchases in non-liquid asset markets are triggered by shocks that prevent banks from fulfilling their regulatory requirements. Each bank's optimal amount of non-liquid assets held on the portfolio is obtained via the constrained optimization outlined in Equations (1) to (4). Hence, for example, in case of a shock which lowers a bank's capital below the regulatory requirement, it liquidates the amount s_i^e which is the difference between the actual amount of non-liquid assets actually held and the new optimal amount of non-liquid assets to be held after the shock occurred. Since each s_i^e is decreasing in p, the aggregate sales function, $S(p) = \sum_i s_i^e(p)$, is also decreasing in p. An equilibrium price is such that total excess demand equal supplies, namely $S(p) = D(p)$. We can define an aggregate demand function $\Theta : [p, 1] \to [p, 1]$: given this function an equilibrium price solves the following fixed point:

$$\Theta(p) = d^{-1}(S(p)) \tag{7}$$

The price convergence process in this case is guaranteed by using the

[15]Convergence is achieved if the financial system does not change between two iterations or if a financial system cycle is detected. A financial system cycle is detected when the adjacency matrix describing the network of interlinkages becomes recurrent or equivalently when all banks in the system repeatedly choose the same portfolio allocation. When a cycle is detected, the probabilities of default are calculated as the average probabilities of default over a cycle, assuming that banks assign the same probability to each financial system in a given cycle.

following inverse demand function:[16]

$$p = exp(-\beta \sum_i s_i^e), \tag{8}$$

where β is a positive constant to scale the price responsiveness with respect to non-liquid assets sold, and s_i^e is the amount of bank i's non-liquid assets sold on the market. Integrating back the demand function in Equation (8) yields the following:

$$\frac{dp}{dt} = \beta S(p) \tag{9}$$

which states that prices will go up in presence of excess demand and downward in presence of excess supply. In the above differential equation β represents the rate of adjustment of prices along the dynamic trajectory.

Tâtonnement on the market for non-liquid assets can be described by the following iterative process. Prior to any shock, the market price for non-liquid assets equals 1, which is the initial price when all banks fulfill their regulatory requirements, and sales of the non-liquid asset are zero. A shock to bank i, say a certain loss of assets, shifts the supply curve upwards, resulting in $S(1) = s_i^e \succ 0$ because bank i starts selling non-liquid assets to fulfill its capital ratio. However, for $S(1)$ the bid price, given by the inverse demand function, Equation (8), equals only $p(S(1))^{bid}$, while the offer price is one. The resulting market price is $p(S(1))^{mid}$, the price in the middle between bid and offer prices. Since the market price thus decreases and banks have to mark their non-liquid assets to market, additional non-liquid asset sales may be needed to fulfill the capital requirement. The step-wise adjustment process continues until the demand and the supply curves intersect at p^*. Note that the supply curve may become horizontal from some value of non-liquid assets sold onwards, as the total amount of non-liquid assets on the banks' balance sheets is limited. Since a shock to a bank will always result in an upward shift of the supply curve, and the

[16] See also Cifuentes, Ferrucci, and Shin [15].

maximum price of the non-liquid asset equals 1, while the initial equilibrium prior to the shock equals zero, a market price $p \in (0, 1)$ always exists. The tâtonnement process on the market for non-liquid assets is displayed on Figure 1.

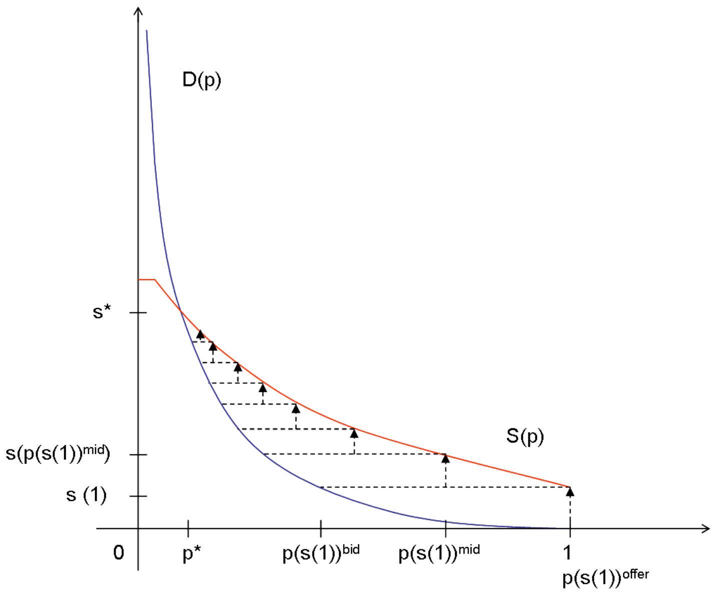

Figure 1: Tâtonnement Process on the Market for Non-liquid Assets

2.4 Equilibrium

Definition. An equilibrium in our model is defined as follows:

(i) A quadruple (l^i, b^i, e^i, c^i) for each bank i that maximizes Equation 1 subject to Equations 2, 3, 4.

(ii) A price in the interbank market, r^{rf}, which is set to equilibrate aggregate supply and demand of funds: $F^{supply} = F^{demand}$.

(iii) A *closest matching partner* clearing mechanism for the interbank market.

(iv) Banks form model equilibrium consistent expectations about $PD^i = prob\left\{er^i < \gamma | c^i < \alpha \cdot d\right\}$.

(v) The price of non-liquid assets solves the fixed point: $\Theta(p) = d^{-1}(S(p))$.

2.5 Systemic Risk Measure

Generally speaking systemic risk occurs in the event in which a shock to one or several institutions spreads to the system in a way that determines the collapse of a large part or the entire system. A prerequisite for the emergence of systemic risk is the presence of inter-linkages and interdependencies in the market, so that the default of a single intermediary or a cluster of them leads to a cascade of failures, which could potentially undermine the functioning of the financial system. The Financial Stability Board, International Monetary Fund, and Bank for International Settlements [28] define systemic risk as "disruption to financial services that is (i) caused by an impairment of all or parts of the financial system, and (ii) has the potential to have serious negative consequences for the real economy." Following this definition, systemic risk is the risk that large parts of the financial system default leading to negative repercussions on the real economy because of a subsequent lack of financial services provision and credit. In our paper we define systemic risk as the proportion of the financial system in default subsequent to a shock which hit banks' assets. As explained above a bank defaults when it is unable to meet regulatory requirements. Recall that banks might default either because they are directly hit by a shock to their asset portfolio which forces them into fire sale spirals or because they have suffered losses to their portfolios due to lack of repayment from other defaulting banks. Systemic risk is then computed as the ratio of assets from all defaulting banks subsequent to a shock to non-liquid assets as from Equation 10:

$$\Phi = \frac{\sum_{def} assets_{def}}{\sum_{i} assets_{i}}, \tag{10}$$

where $def \in i$ indexes banks that are in default after the financial system has absorbed the shock.[17]

[17] Note that the amounts of assets used to compute this measure for systemic risk are taken from the financial system set-up prior to the shock. The reason for this is that the dynamic absorption of the shock in the financial system changes the allocation of assets,

Notice that one could measure banks' individual contributions to systemic risk using an adequate metric. One measure which has been recently proposed to determine contribution to systemic risk is the Shapley value.[18] However, since in our analysis we focus on the interplay of aggregate systemic risk and monetary policy operations, we do not explore banks' individual contributions further.

2.6 Transmission Mechanism, Numerical Algorithm and Calibration

In the model shocks take the form of a loss in banks' non-liquid asset holdings. If subsequent to a shock realization, a bank cannot fulfill its capital requirement, it will transmit the risk in two ways. First, the bank will default on its lending thereby reducing the lending proceeds to exposed banks.[19] Second, banks subject to the shock might need to sell non-liquid assets in order to meet the capital requirements. Upon fire-sales the market price of non-liquid assets falls and this reduces the balance sheets values of other banks that have invested in the same assets. Notice that if upon sale of non-liquid assets the bank hit by the shock is still unable to meet the capital requirement, it will default.

The clearing algorithm for shock transmission is similar to the algorithm used in Cifuentes, Ferrucci, and Shin [15] based on the Eisenberg and Noe [18] clearing algorithm. Upon shock transmission, systemic risk is computed as displayed in Equation 10. All benchmark results presented further below have been computed with a network of 15 banks, but robustness checks have been carried out by increasing the number of banks up to $n = 30$.

potentially resulting in banks having no assets at all when they default.

[18]See Shapley [36]. See also Tarashev, Borio, and Tsatsaronis [14] and Bluhm and Krahnen [31]. Alternative measures of systemic risks are proposed for instance in Adrian and Brunnermeier [10] through a CoVaR methodology. The Shapley value needs to be approximated from a certain number of banks onwards because of a curse of dimensionality.

[19]Note that at the shock transmission stage the interbank links are taken as given, that is, banks do not adjust their lendings and borrowings except for the case of a counterparty default.

The model parameters are chosen to match values observed in the financial system and/or imposed by supervisory policy. The parameter α, the amount of liquid assets banks have to hold as a function of the amount of deposits, is set to 0.1, thus being equivalent to the cash reserve ratio in the U.S. The parameter χ_1, the risk weight for non-liquid assets, is set to 1: this value reflects the risk weight applied in Basel II to commercial bank loans. The parameter χ_2, the weight for interbank lending, is set to 0.2, which is also the risk weight actually applied to interbank deposits between banks in OECD countries. The amount of equities and deposits that banks have initially on their balance sheets is set to 65 billions (mean with variance 10) and 600 billions which is the figure actually found on the balance sheet of the Deutsche Bank in the second quarter of 2012. Following federal reserve bank regulatory agency definitions, banks must hold a capital ratio of at least 8%. Finally, banks return on non-liquid assets is uniformly distributed on the interval between 0% to 15%. The vector of shocks to non-liquid assets is drawn from the multivariate normal distribution Ψ with mean 5, variance of 25 and zero covariance. Note that the variance is set high enough to mimic stress test scenarios. Having a large range is important to capture the effect of all risk channels, in particular the direct interconnection channel.[20] The model parameters are displayed on Table 2.

α	χ_1	χ_2	γ	Deposits	ς	Equity	Yield on NLA	Ψ
0.1	1	0.2	0.08	500	0.01	$N(65, 10)$	$U(0, 0.15)$	$-abs(N(\boldsymbol{mean}, \boldsymbol{\sigma}^2, \boldsymbol{\rho}))$

Table 2: Parameter Values in the Baseline Setting

The table displays the parameter values for our simulations. α is banks' liquidity requirement, χ_1 is the risk weight for non-liquid asset investments, χ_2 is the risk weight for interbank lending, γ is the capital requirement ratio, ς is the amount by which banks overfulfill regulatory requirements, and Ψ is the multivariate normal distribution of the shocks to the financial system (note that shocks between banks are uncorrelated, that is, the covariances between vector elements are zero), with $\boldsymbol{mean} = \boldsymbol{\iota} \cdot 5$, $\boldsymbol{\sigma}^2 = diag(\boldsymbol{\iota} \cdot 25)$, and $\boldsymbol{\rho} = \boldsymbol{\iota} \cdot \boldsymbol{\iota}' \rho - diag(\boldsymbol{\iota} \cdot \rho))$, where $\boldsymbol{\iota}$ is an identity vector of dimension N by 1. N and U designate normal and uniform distributions, respectively.

[20] See Bluhm and Krahnen [31].

3 Systemic Risk and Liquidity with and without Central Bank Intervention

In our numerical simulations we compare results for systemic risk and other synthetic ratios with and without central banks interventions. The number of private banks is set to $N = 15$. We consider this number as representative of a mildly concentrated banking system. In absence of central bank interventions the system is comprised solely of the 15 private banks which trade and achieve equilibrium through the clearing mechanism described above. In presence of a central bank, the latter will supply or withdraw liquidity in the market to guide the interest rate toward a specified target. Note that all results reported as well as confidence intervals given are based on the outcomes from 100 randomly drawn financial systems and shock vectors.

Figure 2 displays a visual outline of a random financial system drawn from the parameter values on Table 2. Each bank is represented by a red ball, with the banks' identifiers in the middle of the ball. The diameter of a ball indicates the bank's size, measured by the sum of its risk weighted assets relative to the sum of all risk weighted assets in the financial system. An arrow pointing from bank A to bank B shows that bank A has lent money to bank B, with the thickness of the arrow indicating the amount of funds lent relative to banks' average equity. Below each of the stylized financial systems there are four further indicators. First, the representative red ball provides the basic measurement unit for banks' size. Second, the thickness of the representative black line provides the basic measurement unit for the size of the lending linkage. Third, the interbank rate is the equilibrium interest rate resulting from the tâtonnement process in the interbank market. Fourth, the non-liquid-assets-to-equity (NLA-E) indicates the average investment (across banks) in non-liquid assets relative to equities. It is computed as the sum of banks' non-liquid asset holdings divided by the sum of equity in the financial system. The ratio gives an indication about the size of banks loan or bond investment relative to their equity Note that lenders provide

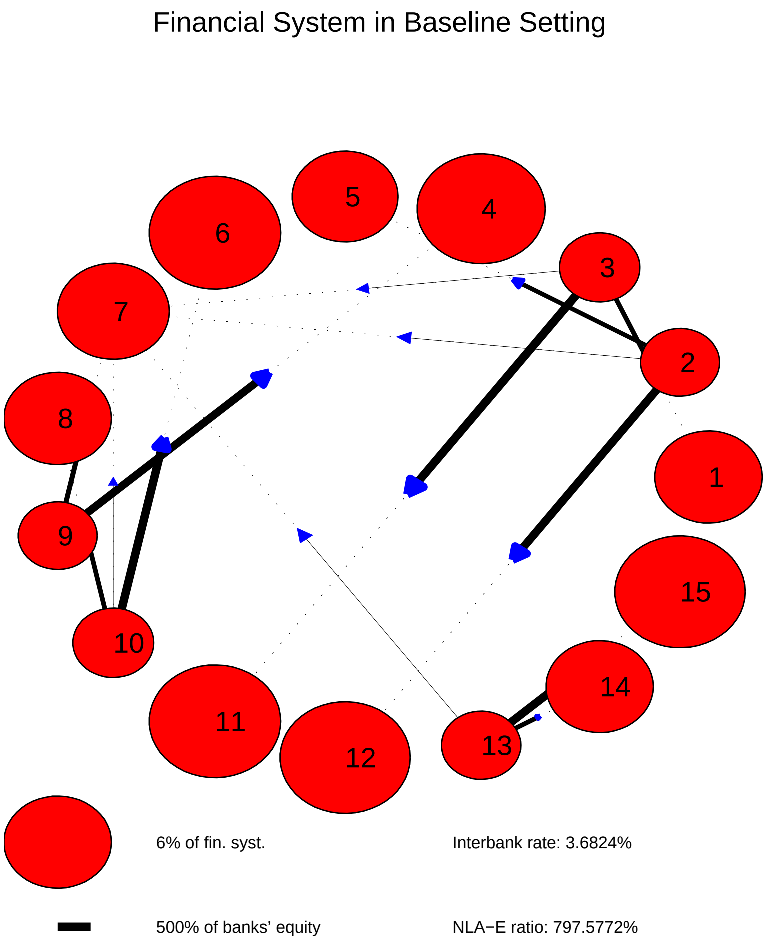

Figure 2: Financial System in Baseline Scenario

The figure displays a random financial system drawn from the parameter values on Table 2. Each bank is represented by a red ball, with the banks' identifiers in the middle of the ball. The diameter of a ball indicates the bank's size, measured by the sum of its risk weighted assets relative to the sum of all risk weighted assets in the financial system. An arrow pointing from bank A to bank B shows that bank A has lent money to bank B, with the thickness of the arrow indicating the amount of funds lent relative to banks' equity. Below each of the stylized financial system there are four further indicators. First, the red ball gives an indication about the percentage of the financial systems a specific ball designates. Second, the thickness of the black line below gives an indication about how much lending a representative arrow designates relative to banks' equity. Third, the interbank rate is the equilibrium interest rate realizing on the interbank market. Fourth, the non-liquid-assets-to-equity (NLA-E) ratio gives an indication about how much banks have invested on average in non-liquid assets relative to their equity.

about 5-6 times their capital on the interbank market. This number is about the same magnitude as in Upper and Worms [40] who analyse the risk of contagion in the German banking system and find that commercial banks lend on average 4.64 times their capital on the interbank market.

To carry out our analysis of the impact of central bank intervention on systemic risk, ee start by describing the evolution of systemic risk and other ratios for different values of the capital requirement with and without central bank interventions. We then highlight the role of central bank interventions. Figure 3 displays the evolution of systemic risk, the ratio of non-liquid asset to equity and the ratio of interbank lending to equities under different values of capital requirements with and without central bank interventions. The ratio of interbank lending to equity is computed as the sum of interbank credits divided by the sum of equity in the financial system. The ratio gives an indication about the size of the interbank market. The dotted lines are the two standard deviation error bands based on 200 draws from the randomly generated financial system and shock distribution,[21] where thresholds are the 5% cut-off points of the most extreme observations of systemic risk obtained conditional on the drawn financial systems and shock vectors.

To understand the evolution of the three metrics of Figure 3, it is important to be aware of a crucial mechanism impacting on the equilibrium allocation in our model: Banks which feature a return on non-liquid assets which is higher than the return on the interbank market, leverage via borrowing from other banks to maximize their profits. Since regulatory requirements impact on banks' capital ratio and therefore potential to leverage, they impact not only on banks' optimal portfolio allocation but also on the equilibrium interbank interest rate and network and therefore ultimately systemic risk.

On Figure 3, the red line displays the evolution of the metrics under consideration without central bank interventions. As the capital requirement

[21] See Table 2 for the assumptions underlying the parameter distributions.

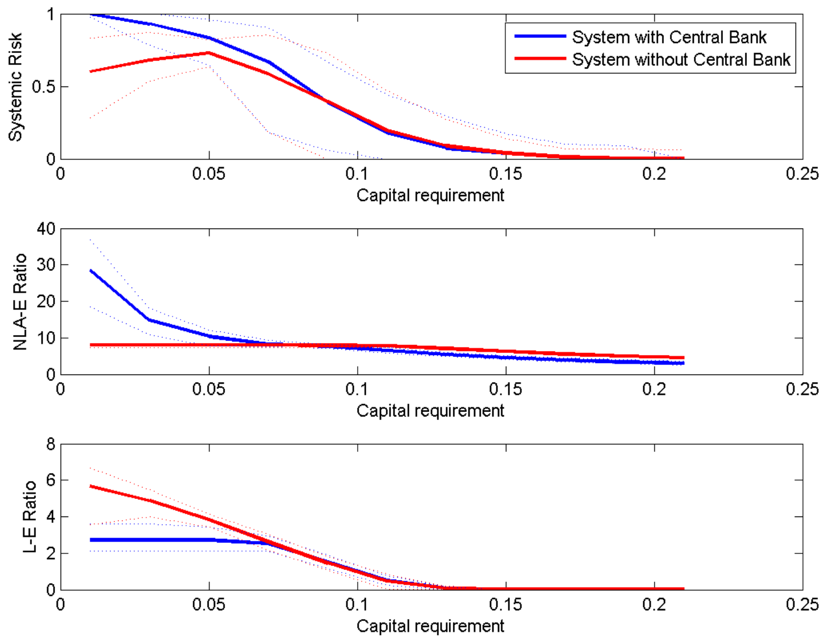

Figure 3: Evolution of systemic risk, ratio of non-liquid asset to equities and ratio of liquid assets to equities under different values of capital requirements and under two scenarios, with and without central bank intervention.

increases, banks can leverage less on the interbank market and therefore invest less in non-liquid assets: the ratio of non-liquid assets (Panel 2) to equities as well as the loan to equity ratio decline (Panel 3). This lowers in tendency systemic risk (Panel 1) because the scope for direct and indirect contagion decreases. However, note that systemic risk features a bell-shaped dynamic. For low levels of γ the extent of interbank lending is large and mostly driven by the banks with high returns on non-liquid assets. Since this drives up the interbank interest rates, only few highly profitable banks borrow large amounts of interbank funds. In this setting the system is 'robust-yet-fragile': if one of the highly leveraged banks is hit by a medium shock, its (many) creditors who each receive a fraction of the shock transmitted can eventually buffer the loss without defaulting. However, a large shock to one of the creditor banks results in the default of a large proportion of the financial system. As the capital requirement is gradually increased, the scope for leveraging is reduced. Therefore the demand from highly profitable banks declines, resulting in a lower interbank interest rate. The lower interest rate in turn increases the number of banks which borrow since their return on non-liquid assets is higher than the return on the interbank market. As the number of borrowers is increased while the number of lenders is reduced, each bank features fewer counterparties on the interbank market. Therefore the robust-yet-fragile property turns more to a fragile system because the shock to one of the (now increased number of) debtor banks is buffered by a lower number of creditors. Therefore systemic risk initially increases with the capital requirement ratio. However, as it is increased beyond 7 percent, the amount of funds exchanged on the interbank market as well as the investment in non-liquid assets decline, ultimately resulting in monotonously decreasing systemic risk.

Let's now analyze the role of central bank intervention (indicated by the blue lines on Figure 3). The supply of liquidity for the overall banking network is higher for cases in which the interbank interest rate increases beyond the central bank interest rate corridor and lower for cases in which the interbank interest rate decreases below the threshold. In particular for low levels of the capital requirement ratio, when the interest rate on the interbank market tends to be above the central bank intervention threshold, the central bank increases liquidity in the system via providing additional funds. This results in a higher non-liquid assets to equity ratio relative to the case without central bank intervention, increasing the scope for contagion via firesales. Therefore, systemic risk is higher with central bank interventions at low capital requirement ratios.

As a robustness analysis of the interplay between regulatory policies, central bank intervention and systemic risk, we repeat our analysis for a range of liquidity requirement ratios. Figure 4 shows the evolution of sys-

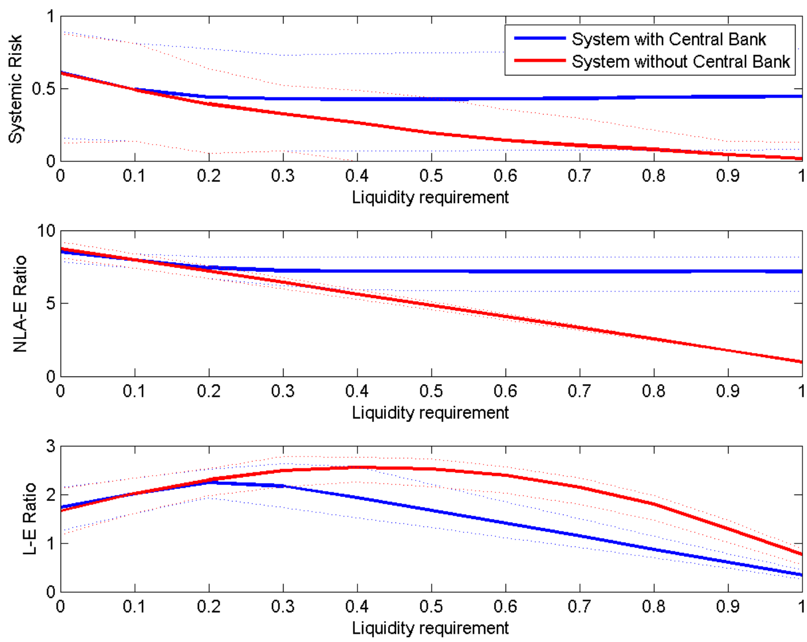

Figure 4: Evolution of systemic risk, ratio of non-liquid asset to equities and ratio of interbank loans to equities under different values of liquidity ratios and under two scenarios, with and without central bank interventions.

temic risk, ratio of non-liquid asset to equities and ratio of interbank loans to equities under different values of liquidity ratios with and without central bank interventions. Again the dotted lines in each panel represent the two standard error bands. The evolution of systemic risk and the other ratios is qualitatively the same across the two scenarios, with and without central bank interventions. As the liquidity requirement increases, banks replace deposits for investing in non-liquid assets with interbank funds which in turn tends to increase the interest rate on the interbank market. In the case of central bank interventions, the central bank starts to supply funds to keep the interest rate within the desired interest rate band. As in the previous analysis, this results in higher non-liquid asset to equity ratios for high liquidity requirement ratios. This ultimately causes systemic risk to be higher when the central bank intervenes because of more contagion through firesales.

Again central bank interventions increase overall systemic risk. As before there is a tension between the beneficial effects of higher liquidity supply, which in this case helps banks to meet the liquidity requirements, and the increase in risk taking. Overall the increase in risk taking tends to prevail.

4 Conclusion

There is a vivid debate on whether central bank interventions can mitigate or amplify systemic risk in the market. A tension materializes between the positive impact of interest rate stabilization and higher loan supply and the decrease in the cost of short term banks' liabilities which could increase banks' risk taking and increase the likelihood of cascading defaults. We analyze this tension within a network model of the interbank market. Banks provide demand for loans by solving portfolio optimization problems. Cross-exposure in the interbank market provides interconnections that allow for the diffusion of risk through network externalities. Diffusion of shocks and endogenous defaults in our model is also linked to the fact that all banks invest in non-liquid assets whose swings in market price capture pecuniary externalities. This paper contributes to a new strand of the literature on monetary policy that focuses on interacting banks with a clear objective function. Several features that have gained prominence during the past couple of years emerge in our simulations. For example, the interest rate targeting rule imposed on our central bank forces the central bank to provide liquidity to banks when ever there is significant shock to their illiquid asset holdings, e.g. loans or securities. Through a liquidity insurance channel, we find banks to increase risk taking, consistent with the risk-taking channel proposed by Adrian and Shin [3]. Through this channel, central banks' interventions in the market can amplify systemic risk. The bank funding implications of the monetary policy rule we are assuming - interest rate targeting- motivates banks to take higher risks if they face negative asset value shocks. We think that our model displays some unintended consequences of monetary policy that are imminent if the banking system is highly interconnected, and there is a risk of significant asset value shock.

This paper is one of the first to model the interplay of regulatory and monetary policy. Our model specifies a particular regulatory regime, imposing constraints on bank behavior. These restrictions concern leverage (minimum capital requirement) and maturity transformation (mimimum liqudity requirement). We have chosen the parameters of the regime to resemble current capital and liquidity standards. A comparative analysis of regulatory regimes is left for future work. Equally, an analysis of different policy regimes, imposed on the central bank, is left for future work.

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5 Appendix A: Banks' Objective Function

Bank i's expected profit is outlined in Equation 11:

$$E(\pi^i) = E(\pi^{lending^i}) + E(\pi^{e^i}) - E(cost^{borrowing^i}), \tag{11}$$

where

- $E(\pi^{lending^i})$ is bank i's expected profit from lending funds on the interbank market,
- $E(\pi^{e^i})$ is bank i's expected profit from investments into non-liquid assets, and
- $E(cost^{borrowing^i})$ is bank i's expected cost for borrowing funds on the interbank market.

Bank i's expected profit is thus related to two different asset classes: derivative investments (non-liquid assets) and interbank lending. Consider first the interbank market. In our model the interest rate on the interbank market consists of two components: the first component is the risk-free rate, r^f, which purely reflects the cost of intertemporal transfer of funds between counterparties, regardless of any insolvency risk. The second component is a premium, r^{PD}, which reflects the probability of default of the borrowing bank. Thus, the overall cost for bank j to borrow an amount b^j on the interbank market is

$$E(cost^{bb^j}) = (r^f + r^{PD^j}) \cdot b^j. \tag{12}$$

To shed more light on the risk premium charged for borrowing money consider banks' lending decision. Note that lending banks charge a fair risk premium which reflects the counterpart's actual probability of default. A bank i engaging in interbank lending has the following expected profit from providing an amount of money, l^{ij}, on the interbank market to bank j:

$$E(\pi^{bl^{ij}}) = (1-PD^j)\cdot l^{ij}\cdot(r^{rf}+r^{PD^j}) + PD^j\cdot(l^{ij}-\xi l^{ij})\cdot(r^{rf}+r^{PD^j}) \quad (13)$$

where PD is a bank's probability of default and ξ, $0 \leq \xi \leq 1$ is the loss-given-default ratio which captures that only a fraction of the outstanding amount is paid back in case of the debtor's default. The first product in Equation (13) reflects the lender's profit in case the debtor does not default, and the second term reflects the case when the debtor defaults.

Since creditors charge a fair risk premium for debtors' probability of default, their expected profit from lending must be equal to the profit they obtain in the absence of risk, that is,

$$E(\pi^{bl^{ij}}) = l^{ij}\cdot r^{rf}. \quad (14)$$

Replacing $E(\pi^{bl^{ij}})$ by $l^{ij}\cdot r^{rf}$ in Equation 13 and solving for r^{PD} yields

$$r^{PD^j} = \frac{\xi PD^j}{1-\xi PD^j}\cdot r^{rf} \quad (15)$$

which is the fair premium charged on the interbank market for banks' individual default risk.

We assume that banks' individual probability of default is publicly known. Using Equations 12 and 15. Bank i's expected cost of borrowing is thus equal to

$$E(cost^{b^i}) = (r^f + r^{PD^i})\cdot b^i = b^j\cdot r^f\cdot\frac{1}{1-\xi PD^i}. \quad (16)$$

Next, bank i's overall expected profit from lending is given by the sum of individual amounts lent to its counterparties:

$$E(\pi^{l^{i\cdot}}) = \sum_{1:h\in J} E(\pi^{l^{ih}}), \quad (17)$$

where $\cdot$ indicates several counterparties, $1:h \in J$ are the h banks bank i has lent money to, from the set of all banks J not including bank i. Taking the sum over h in Equation 13 and using Equation 15, it can be shown that Equation 17 simplifies to

$$E(\pi^{l^{i\cdot}}) = l \cdot r^{rf}, \tag{18}$$

where $l = \sum_{1:h \in J} \cdot l^{ih}$. Equation 18 reflects that banks charge fair risk-premia, that is, in expectation the losses resulting from the default of some counterparties are compensated by risk premia paid by banks that actually do not default. As a result, the expected yield from bank lending is equal to the risk free rate.

Finally, bank i's expected return is also linked to its non-liquid asset investments which is related to derivative investments. Bank i's expected return from investments into non-liquid assets is given by

$$\frac{r^i}{p} \cdot e^i, \tag{19}$$

where r^i is bank i's yield on non-liquid asset investments, e^i is bank i's investment in non-liquid assets, and p is the market price of the non-liquid asset. Note that banks' yield is divided by the market price of the non-liquid asset –which is initially set to 1– to reflect that the yield has an inverse relation with the market price. This is the case for financial products which feature fixed payoffs such as bonds. Since the market price of non-liquid assets can change in our model and banks can re-optimize their portfolio, we include this feature in the objective function.

Using equations 16, 18, and 19 banks i's objective function, equation 11, can be expressed as

$$E(\pi^i) = l \cdot r^{rf} + \frac{r^i}{p} \cdot e^i - b^i \cdot r^f \cdot \frac{1}{1 - \xi PD^i}. \tag{20}$$

Note that in expectation banks' return from lending, r^f, is smaller than their cost of borrowing, $r^f \cdot \frac{1}{1-\xi PD^i}$. This difference emerges because because banks always have to pay a fair risk premium for borrowing (as long as they do not default) but do not expect to get back all the funds they lend because in expectation some of their counterpart debtors will default. In case all borrowing banks' probability of default is zero, expected borrowing and lending cost are the same.