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# Systemic risk in a network model of interbank markets with central bank activity

by

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**Abstract**

The breakdown of the interbank money markets in the face of the recent financial crisis has forced central banks and governments to take extraordinary measures to sustain financial stability. In this paper we investigate which influence central bank activity has on interbank markets. In our model, banks optimize a portfolio of risky investments and riskless excess reserves according to their risk and liquidity preferences. They are linked via interbank loans and face a stochastic supply of household deposits. We then introduce a central bank into the model and show that central bank activity enhances financial stability. We model the default of a large bank and analyse the resulting contagion effects. This is compared to a common shock that hits banks who have invested in similiar assets. Our results indicate that common shocks are not subordinate to contagion effects, but are instead the greater threat to systemic stability.

*Keywords:* systemic risk, interbank markets, monetary policy, contagion, common shocks

JEL classification: C63, E52, E58, G01, G21

## 1. Introduction

The onset of the financial crisis has highlighted the importance of interbank money markets for financial stability. In normal times, banks with excess liquidity provide interbank loans to banks with a liquidity demand. This interconnection of the banking system can lead to an enhanced liquidity allocation and increased risk sharing amongst the banks, as e.g. Allen and Gale (2000) show. Rochet and Tirole (1996), Furfine (2001), or Freixas and Holthausen (2005) however, argue that interbank markets are characterized by asymmetric information and are hence incomplete. Furthermore, Freixas and Jorge (2008), Brunnermeier (2008) and Allen et al. (2009) show that there are various sources for disturbances on interbank markets. The default of the american investment bank Lehman Brothers in September 2008 and the subsequent turmoil on the interbank market was such a disturbance. The insolvency of Lehman Brothers led to an increase of banks' risk awareness and risk aversion and ultimately to the breakdown of the interbank money market.

As a result the risk premia for unsecured interbank loans (as can be seen e.g. in the spread between the 3 month EUREPO and 3 month EURIBOR) increased drastically and resulted in a massive impairment of bank's liquidity provision (see e.g. Heider et al. (2009), Brunnermeier (2008)). Central banks were forced to undertake unprecedented non-standard measures to reduce money market spreads and ensure liquidity provision to the banking system. Lenza et al. (2010) argue that quantitative and qualitative easing acted indeed mainly through their effect on money market spreads, effectively reducing them. This is consistent with Allen et al. (2009) and Freixas et al. (2010), who show that central bank intervention can increase the efficiency of interbank markets and reduce liquidity risks. From these results it is clear, that a realistic model of interbank markets has to take the central bank into account.

Even though the immediate threat of a systemic failure seems to have ceased, the non-standard measures of many central banks are still in place and systemic risk remains a pressing issue. There is a vast literature on

systemic risk, that is rapidly growing since the onset of the financial crisis. Bandt et al. (2009) distinguish between a broad and a narrow sense of systemic risk. In their nomenclature contagion effects on interbank markets pose a systemic risk in the narrow sense, whereas the broad sense of systemic risk is characterized as a common shock to the financial markets, that affects many institutions or markets. A large part of the literature on systemic risk focuses on systemic risk through contagion effects. Rochet and Tirole (1996) for instance state that *"Systemic risk refers to the propagation of an agent's economic distress to other agents linked to that agent through financial transactions."*, emphasizing the role of interbank markets for systemic risk. Iori et al. (2006) present a network model of interbank markets and analyze the effects of the bank sectors' heterogeneity on financial stability. Financial networks and especially interbank markets exhibit a robust-yet-fragile property, as for example Haldane (2009) argues. This behaviour of connected networks can be best explained as a knife-edge property. Up to a certain point, financial networks and interbank connections serve as a mutual insurance of the financial system and thus contribute to systemic stability. Beyond this point the same interconnections might serve as a shock-amplifier and thus increase systemic fragility. This is in line with Fernando (2003), Cifuentes et al. (2005) and Gai and Kapadia (2008) who argue that increasing connectivity on the interbank market leads to increasing contagion in times of crisis.

The broad sense of systemic risk (as defined by Bandt et al. (2009)) has become increasingly important in recent years. Adrian and Shin (2008) address the issue of financial contagion through fire-sales and marked-to-market accounting and argue that this can amplify the potential impact of a shock and therefore pose a systemic risk. Acharya (2009) models systemic risk as the endogenously chosen correlation of returns on assets held by banks. Two types of externatlities are introduced: if a bank fails, there is a reduction of aggregate deposit supply in the economy, resulting in a reccessionary spillover (a negative externality). The surviving banks, however, have a strategic benefit from the failure of other banks (positive externality) due to an increase in scale, resulting from the migration of the failed bank's depositors. Banks strategically decide to invest in similiar assets if the negative externality exceeds the positive externality. In this case there is a correlation between the bank's assets which exposes them to common shocks. Acharya (2009) defines systemic risk as *"the joint failure risk arising from the correlation of returns on asset side of bank balance sheets"*. Acharya argues that bank regulation

mechanisms that are based on a bank's own risk only might fail to mitigate systemic risk. The conclusion is that common shocks are not subordinated to contagion, but are in fact a coequal form of systemic risk. Whelan (2009) argues in the same direction, giving a simple example where a small initial trigger leads to a large common shock. Wagner (2009) states that one key reason behind the severity of the financial crisis of 2007/2008 was that many financial institutions had invested in the same assets (e.g. subprime mortgages), therefore exposing them to a common shock. Irrespective of their importance, common shocks have not yet received the same attention in the literature, as contagion has.

A prerequisite for financial crisis prevention and management is to assess both types of systemic risk in an appropriate framework. Brunnermeier et al. (2009) propose to apply leverage, maturity mismatch or the rate of expansion to measure systemic risk. Lehar (2005) estimates the risk of a common shock by the correlation between institution's asset portfolios. Acharya et al. (2009) recommends to measure an institution's contribution to aggregate risk based on it's marginal value-at-risk and it's marginal expected shortfall. Acharya et al. (2010) propose to assess the systemic expected shortfall which indicates how much an institution is prone to undercapitalize when the financial system is undercapitalized as well. Haldane (2009) suggests to measure contagion based on the interconnectedness of each institution within the financial system, whereas Adrian and Brunnermeier (2009) focus on Co-VaR, which is the value-at-risk of the whole financial sector in times of crisis. They argue to interpret the difference between CoVar and the institution's specific value-at-risk as the institution's contribution to systemic risk. Tarashev et al. (2009) propose to apply the Shapley value methodology to asses this contribution. Thomson (2009) provides a scoring model to categorize each institution according to it's contribution to systemic risk. Eligible criteria are size, contagion, correlation, concentration and economic conditions.

A new approach to systemic risk in financial markets comes from network theory. As for example Allen and Babus (2008) argue, linkages between financial institutions stem from both the asset side (through holding similiar portfolios) and the liabilities side (by sharing the same mass of depositors). These linkages can be direct (as in the case of interbank loans) and indirect (as in the case of similiar portfolios). Allen and Babus (2008) investigate the resilience of financial networks to shocks and the formation of

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financial networks. Network theory has been successfully applied in the analysis of payment systems (see e.g. Soramäki and Galbiati (2008) or Markose et al. (2010)). Castrén and Kavonius (2009) apply network theory to study accounting-based balance sheet interlinkages at a sectoral level. Canedo and Jaramillo (2009) propose a network model to analyse systemic risk in the banking system that seeks to obtain the probability distribution of losses for the financial system resulting both from the shock/contagion process. Nier et al. (2007) construct a network model of banking systems and find that (i) the better capitalised banks are, the more resilient is the banking system against contagious defaults and this effect is non-linear; (ii) the effect of the degree of connectivity is non-monotonic; (iii) the size of interbank liabilities tend to increase the risk of knock-on default; and (iv) more concentrated banking systems are shown to be prone to larger systemic risk. In Gai and Kapadia (2009) the authors investigate systemic crises with a network model and show that on the one hand the risk of systemic crises is reduced with increasing connectivity on the interbank market. On the other hand, however, the magnitude of systemic crises increases at the same time.

Even though these new results indicate that common shocks are not subordinated to contagion, a large fraction of the existing literature focuses solely on systemic risk through contagion and therefore underestimates systemic risk that stems from common shocks. Network models of interbank markets may contribute to a deeper understanding of both types of systemic risk. But these models often suffer from their very own problems. Many assumptions about how agents behave are ad-hoc and not well enough rooted in fundamental principles. Moreover, agents often behave very mechanistic and therefore limit the flexibility that one wants to obtain by using network models and multi-agent simulations. To overcome these obstacles, we develop a model of interbank markets that fulfills three criteria: (i) the behaviour of agents has to be well rooted in fundamental principles; (ii) both types of systemic risk can be analyzed; and (iii) the central bank has to be included in the model since it has a major influence on interbank markets. The rest of the paper is organized as follows. Section 2 describes our model in detail, 3 presents the results of our numerical simulations, while section 4 concludes and derives policy implications.

## 2. The Model

Iori et al. (2006) develop a network model of the banking system, where agents (banks) can interact with each other via interbank loans. The balance sheet of banks consits of risk-free investments and interbank loans as assets and deposits, equity and interbank borrowings as liabilities. Banks channel funds from depositors towards productive investment. They receive liquidity shocks via deposit fluctuations and pay dividends if possible. Nier et al. (2007) describe the banking system as a random graph where the network structure is determined by the number of nodes (banks) and the probability that two nodes are connected. The bank's balance sheet consists of external assets (investments) and interbank assets on the asset side and net worth, deposits and interbank loans as liabilities. Net worth is assumed to be a fixed fraction of a bank's total assets and deposits are a residual, designed to complete the bank's liabilities side. Shocks that hit a bank and lead to it's default are distributed equally amongst the interbank market.

Both authors assume a risk-free investment opportunity and Nier et al. (2007) assume deposits to be a residual. But since fluctuations in investment returns have to be compensated by banking capital, risky investments are a major cause of bank insolvencies. Because of the maturity transformation that banks perform and since deposits usually have a short maturity, deposit fluctuations are a further cause of bank insolvencies. If suddenly depositors want to withdraw more deposits from the bank, than the bank has liquid funds, this bank will become illiquid and goes into insolvency. A model of systemic risk has therefore to take into account both, risky assets and deposit fluctuations as possible sources of knock-on effects, contagion and systemic risk.

We follow Iori et al. (2006) and Nier et al. (2007) in some aspects and develop a network model of interbank markets. However, we explicitly allow the possibility of risky investments and deposit fluctuations. We furthermore include a central bank in our model, since it is evident from the literature that monetary policy has a large influence on interbank markets. Our model allows us to investigate direct contagion effects as well as common shocks.

## 2.1. Balance Sheets

We start with the balance sheet of a bank $k$ that holds risky investments $I^k$ and riskless excess reserves $E^k$ as assets at every point in (simulation-) time $t = 1 \ldots \tau$. The investments of bank $k$ have a random maturity $\tau_I^k > 0$ and we assume that each bank finds enough investment opportunities according to it's preferences. The bank refinances this portfolio by deposits $D^k$ (which are stochastic and have a maturity of zero), from which it has to hold a certain fraction $rD^k$ of required reserves at the central bank, fixed banking capital $BC^k$, interbank loans $L^k$ and central bank loans $LC^k$. Interbank loans and central bank loans are assumed to have a maturity of $\tau_L^k = \tau_{LC}^k = 0$. The maturity mismatch between investments and deposits is the standard maturity transformation of commercial banks. Interbank loans can be positive (bank has excess liquidity) or negative (bank has demand for liquidity), depending on the liquidity situation of the bank at time $t$. The same holds for central bank loans, where the bank can use either the main refinancing operations to obtain loans, or the deposit facility to loan liquidity to the central bank. The balance sheet of the commercial bank therefore reads as:

$$I_t^k + E_t^k = (1 - r)D_t^k + BC_t^k + L_t^k + LC_t^k \tag{1}$$

The interest rate for deposits at a bank is $r^d$ and the interest rate for central bank loans is $r^b$. Note that we have not distinguished between an interest rate for the lending and deposit facility and therefore the interest rate on the interbank market will be equal to the interest rate for central bank loans.

The banks decide about their portfolio structure and portfolio volume. We have assumed a constant relative risk aversion (CRRA) utility function to model the bank's preferences:

$$u^k = \frac{1}{1 - \theta^k} \left( V^k (1 + \lambda^k \mu^k - \frac{1}{2}\theta^k (\lambda^k)^2 (\sigma^2)^k) \right)^{(1-\theta^k)} \tag{2}$$

where $\lambda^k$ is the fraction of the risky part of the portfolio, $\mu^k$ is the expected return of the portfolio and $\theta^k$ is the banks risk aversion parameter. $V_t^k = I_t^k + E_t^k$ denotes the bank's portfolio volume. The risky part of the portfolio follows from utility maximisation and reads as:

$$(\lambda^k)^* = \min \left\{ \frac{\mu^k}{\theta^k (\sigma^2)^k}, 1 \right\} \quad \in [0, 1] \tag{3}$$

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The portfolio volume can be obtained by similiar measures as:

$$(V^k)^* = \left[ \frac{1}{r^b} \left( \left( 1 + \lambda^k \mu^k - \frac{1}{2} \theta^k (\lambda^k)^2 (\sigma^2)^k \right)^{(1-\theta^k)} \right) \right]^{1/\theta^k} \tag{4}$$

where $r^b$ denotes the refinancing cost of the portfolio. Since banks obtain financing on the interbank market and at the central bank at the same interest rate, this refinancing cost is equal to the main refinancing rate. It is possible to introduce a spread between the lending and deposit facility and therefore allowing the interest rate on the interbank market to stochastically vary around the main refinancing rate. If a bank now plans it's optimal portfolio volume, it calculates with a planned refinancing rate. This refinancing rate follows from the bank's plan about how much interbank loans it wants to obtain on the interbank market at a planned refinancing rate and how much central bank loans it plans to obtain at the main refinancing rate. If this plan cannot be realized (e.g. if a bank's liquidity demand is unsatisfied on the interbank market), banks make a non-optimal portfolio choice. For the sake of simplicity we want to exclude this possibility. Note that we do not model an explicit market for central bank money. The central bank rather accomodates all liquidity demands of commercial banks, as long as they can provide the neccessary securities. This assumption is not unrealistic in times of crises, as for example the full allotment policy of the ECB shows.

### 2.2. Update Algorithm

In our simulation we have implemented an update algorithm that determines how the system evolves from one state to another. The algorithm is divided up into three phases that are briefly described here. Every update step is done for all banks for a given number of sweeps. At the beginning of phase 1 the bank holds assets and has liabilities from the end of the previous period:

$$\underline{I}^k_{t-1} + \underline{E}^k_{t-1} + r\underline{D}^k_{t-1} = \underline{D}^k_{t-1} + \underline{BC}^k_{t-1} + \underline{L}^k_{t-1} + \underline{LC}^k_{t-1} \tag{5}$$

where an underline denotes realized quantities. In period 0 all banks are endowed with initial values. The update step starts with banks getting the required reserves $r\underline{D}^k_{t-1}$ and excess reserves $\underline{E}^k_{t-1}$ plus interest payment from the central bank (we have assumed that for both required and excess reserves an interest of $r^b$ is paid). The banks obtain a stochastic return for

all investments $\underline{I}^k_{t-1}$ which might be either positive or negative. The firms furthermore pay back all investments $\underline{I}^k_f$ that were made in a previous period and have a maturity of $\tau^k_I = 0$. The banks then pay interest for all deposits that were deposited in the previous period. After that the banks can either receive further deposits from the households, or suffer deposit withdrawings $\Delta D^k_t$. At the end of the first period, all interbank and central bank loans plus interests are paid either to, or by bank $k$.

At the beginning of phase 2, the bank's liquidity $\widehat{Q}^k$ is therefore given as:

$$
\begin{aligned}
\widehat{Q}^k_t = {} & (1+r^b)\left[r\underline{D}^k_{t-1} + \underline{E}^k_{t-1}\right] + \mu^k \underline{I}^k_{t-1} + \underline{I}^k_f - r^d \underline{D}^k_{t-1} \pm \Delta D^k_t \quad (6) \\
& -(1+r^b)\left[\underline{L}^k_{t-1} + \underline{LC}^k_{t-1}\right] + \underline{BC}^k_{t-1}
\end{aligned}
$$

All banks with $\widehat{Q}^k_t < 0$ are marked as illiquid and removed from the system. Banks that pass the liquidity check now have to pay required reserves $r\underline{D}^k_t$ to the central bank.

In phase 3 the bank $k$ determines it's planned level of investment $I^k_t = (\lambda^k)^*(V^k)^*$ and excess reserves $E^k_t = (1 - (\lambda^k)^*)(V^k)^*$ according to equations (3) and (4). From this planned level and the current level of investments (all investments that were done in earlier periods and have a maturity $\tau^k_I > 0$), as well as the current liquidity (6) the bank determines it's liquidity demand (or supply). If a bank has a liquidity demand, it will go first to the interbank market, where it asks all banks $i$ that are connected to $k$ (denoted as $i:k$), if they have a liquidity surplus. In this case the two banks will interchange liquidity via an interbank loan. We adopt the convention, that a negative value of $L$ denotes a demand for liquidity and therefore the interbank loan demand of bank $k$ is given by:

$$
L^k_t = \widehat{Q}^k_t - I^k_t \quad (7)
$$

From this, one can obtain the realized interbank loan level, via the simple rationing mechanism:

$$
\underline{L}^k_t = \min \left\{
\begin{array}{llll}
L^k_t , & -\sum_{i:k} L^i_t & | \quad L^i_t \cdot L^k_t < 0 & ; \quad \text{if } L^k_t > 0 \\
-L^k_t , & \sum_{i:k} L^i_t & | \quad L^i_t \cdot L^k_t < 0 & ; \quad \text{if } L^k_t < 0
\end{array}
\right\} \quad (8)
$$

Now there are three cases, depending on the bank's liquidity situation. If a bank has neither a liquidity demand nor excess liquidity, it will not interact

with the central bank and this step is skipped. However, if the bank still has a liquidity demand, it will ask for a central bank loan:

$$LC_t^k = \underline{L}_t^k - L_t^k \tag{9}$$

The central bank then checks if the bank has the neccessary securities and if so, it will provide the loan:

$$\underline{LC}_t^k = \max\left(LC_t^k, -\alpha^k \underline{I}_{t-1}^k\right) \tag{10}$$

where $\alpha^k \in [0,1]$ denotes the fraction of investments of bank $k$ that are accepted as securities by the central bank. If a bank has insufficient securities, the central bank will not provide the full liquidity demand and the bank has to reduce the planned investment and excess reserve level. If the bank has no securities (no investments $\underline{I}_{t-1}^k$), it cannot borrow from the central bank. This rationing mechanism maps planned investment levels to realized ones.

The second case is that a bank has a large liquidity surplus even if all planned investments can be realized. In this case, the bank is able to pay dividends $A_t^k$ and the dividend payment is determined by:

$$A_t^k = \min\left\{LC_t^k, \beta^k \underline{I}_t^k\right\} \tag{11}$$

where $\beta^k \in [0,1]$ is the dividend level of bank $k$. The dividend level will typically be close to 1 as shareholders will push the bank to rather pay dividends than use the money to deposit it at the central bank at low interest rates. The remaining:

$$\underline{LC}_t^k = LC_t^k - A_t^k \tag{12}$$

is transferred to the central bank's deposit facility. Finally the realized investments are transferred to the firm sector and the realized excess reserves are transferred to the central bank.

These steps are done for all $k = 1 \ldots N$ banks in the system for $t = 1 \ldots \tau$ time steps. As there are two stochastic elements in the simulation (the return of investments and the deposit level) we have modeled two channels for a banks insolvency. The first is via large deposit withdrawals. As deposits are very liquid and investments are illiquid for a (in our model random) investment time, this maturity transformation might lead to illiquidity and therefore to insolvency. The second channel for insolvency is via losses on

investments. If the banks banking capital is insufficient to cover losses from a failing investment, this bank will be insolvent. If a bank fails, all the banks that have loaned to this bank will suffer losses, which they have to compensate by their own banking capital. This is a possible contagion mechanism, where the insolvency of one bank leads to the insolvency of other banks, that would have survived if it was not for the first bank's insolvency.

### 2.3. Model Parameters

There are eightteen model parameters that control our numerical simulation. If not stated otherwise, our numerical simulations were performed with the parameters given in this section. We performed our simulation with $N = 100$ banks and $\tau = 500$ update steps each. We repeated every simulation `numSimulations=100` times to average out stochastic effects. The interest rate on the interbank market was chosen to be $r^d = 0.02$ and the main refinancing rate as $r^b = 0.04$. The required reserve rate is $r = 0.02$. With `connLevel`$\in [0, 1]$ we denote the level of interbank connections and therefore control the basic network structure. At a `connLevel=0` there is no interbank market and at `connLevel=1` every bank is connected to every other bank.

Two sets of parameters are used to describe the influence of the real economy on the model. The first set is the probability that a credit is returned successful, $p_f = 0.97$. The return for a successful returned credit is $\rho_f^+ = 0.09$ and in case a credit defaults, the negative return on the investment is $\rho_f^- = -0.05$. To plan their optimal portfolio, the banks have an expected credit success probability $p_b$ and expected credit return $\rho_b^+$. We assumed that these expected values correspond to the true values from the real economy. The optimal portfolio structure and volume of a bank depends also on it's risk aversion parameter $\theta$. We chose $\theta \in [1.67, 2.0]$ randomly for each bank to account for heterogeneity in the banking sector.

Deposit fluctuations $\Delta D_t^k$ were modelled as:

$$\Delta D_t^k = (1 - \gamma^k + 2\gamma^k x)\underline{D}_{t-1}^k \tag{13}$$

where $\gamma^k = 0.02$ is a scale factor and $x \in [0, 1]$ being a random number. From this one can deduce $(1 - \gamma^k)\underline{D}_{t-1}^k \leq \underline{D}_t^k \leq (1 + \gamma^k)\underline{D}_{t-1}^k$. The fraction of a bank's investments that the central bank accepts as securities is set to $\alpha^k =$
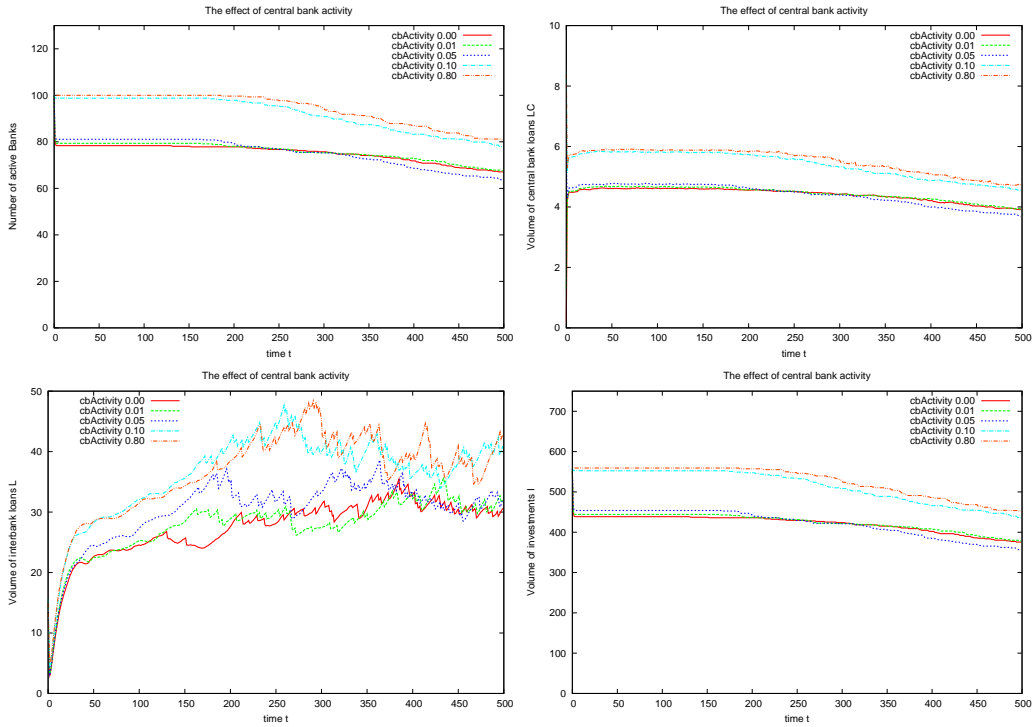
Figure 1: The effect of central bank activity. Top left: number of active banks over simulation time for different values of $\alpha^k$. Bottom left: volume of interbank loans $L$ over simulation time for different values of $\alpha^k$. Top right: volume of central bank loans $LC$ over simulation time for different values of $\alpha^k$. Bottom right: volume of investments to the real economy over simulation time for different values of $\alpha^k$. We used $\rho_f^- = -0.08$ and the parameters given in section (2.3) otherwise.

0.8, assuming that banks invest only in assets which have a good rating. The level of dividends $\beta^k$ that a bank pays to its shareholders was chosen as $\beta^k = 0.99$ which implies that shareholders can find more attractive investment opportunities than the central bank's deposit facilitiy (which would be the alternative investment for the bank).

## 3. Results

Central bank intervention can increase the efficiency of interbank markets, as for example Allen et al. (2009) and Freixas et al. (2010) show. We therefore investigate the effects of central bank intervention on financial stability. In figure (1) we have shown the simulation results for the parameters

given in section (2.3) and a varying level $\alpha^k \in [0.0, 0.8]$ of central bank activity. We have chosen $\rho_f^- = -0.08$ since with $\rho_f^- = -0.05$ very few bank insolvencies occur and no stabilizing effect can be visible. From the results in figure (1) one can see three things. First of all, with increasing central bank activity the number of bank insolvencies decreases. This emphasizes the stabilizing effect that the central bank has on the financial system and is in accordance with Allen et al. (2009) and Freixas et al. (2010). Second, there is only little difference between $\alpha^k = 0.1$ and $\alpha^k = 0.8$ which means that it is sufficient for the stabilizing effect of central bank activity if the central bank accepts only a small fraction of bank's assets as securities. And third, there is a slight increase in the interbank market liquidity with increasing central bank activity, leading to the conclusion that the central bank can indeed enhance the liquidity allocation of interbank money markets. Our results indicate therefore that central bank activity both enhances financial stability and liquidity provision on the interbank market.

We have also investigated the effect of the interbank network structure on financial stability. We have therefore introduced the interbank connection level `connLevel` to vary the degree of connectivity on the interbank market. The results of this analysis are depicted in figure (2). Our results show that financial stability increases with increasing connection level and that this increase is monotonous. Our results indicate that the relation between interbank liquidity and connection level is non-monotonic. For very low connection levels there is only very little activity on the interbank market. As the connection level increases, the activity on the interbank market increases up to a certain point. For higher connection levels the activity on the interbank market decreases again. Since large interbank lending levels increase the susceptibility to knock-on effects, this is consistent with the results of Iori et al. (2006) and Nier et al. (2007) who show that the relation between interbank connectivity and knock-on effects is non-monotonic.

In figure (3) we have depicted the effects of a varying average risk aversion parameter. We have kept the lower boundary for $\theta^k$ fixed at 1.67. For this $\theta$ we obtain with our values for $\rho_b^+$ and $p^b$ a $\lambda^k \simeq 0.99$, for smaller $\theta$ values we would obtain a $\lambda^k = 1.0$ and banks would hold no excess reserve. Since this is not very likely, we have chosen this lower bound. The upper bound is varied and we have simulated for an upper $\theta^k = 2.0$, $\theta^k = 3.0$ and $\theta^k = 4.0$. With increasing average risk aversion the stability of the financial system
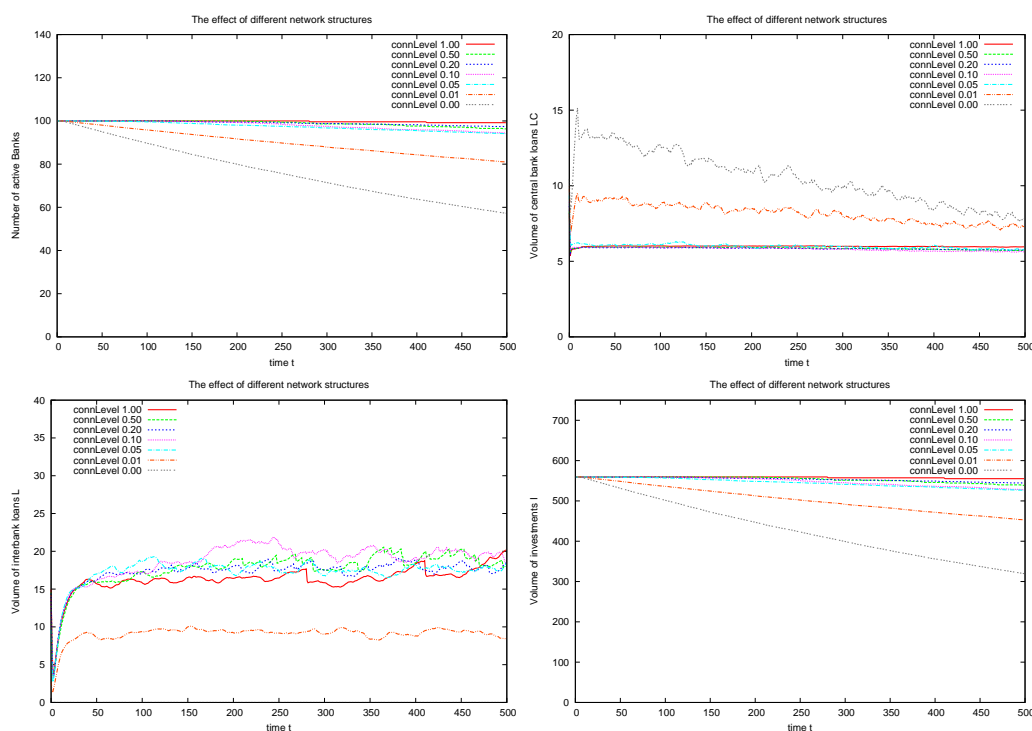
13

Figure 2: The effect of different network structures. Top left: number of active banks over simulation time for different values of `connLevel`. Bottom left: volume of interbank loans $L$ over simulation time for different values of `connLevel`. Top right: volume of central bank loans $LC$ over simulation time for different values of `connLevel`. Bottom right: volume of investments to the real economy over simulation time for different values of `connLevel`. We used the parameters given in section (2.3).

increases and fewer banks go into insolvency. As can be seen from figure (3) the level of investments into the real economy decreases with increasing risk aversion which is a direct consequence of the bank's portfolio choice. If one is interested in a high investment level, one has to take two countervailing effects into account. On the one hand, with increasing risk aversion, more banks are active (fewer go into insolvency) and a larger absolute number of banks can do investments. On the other hand decreases the fraction of the risky portfolio with increasing average risk aversion. From figure (3) it can be seen that this decrease in the risky portfolio exceeds the stabilizing effect and that the total investment level decreases with increasing risk aversion.

Iori et al. (2006) argue that an increasing heterogeneity in the financial
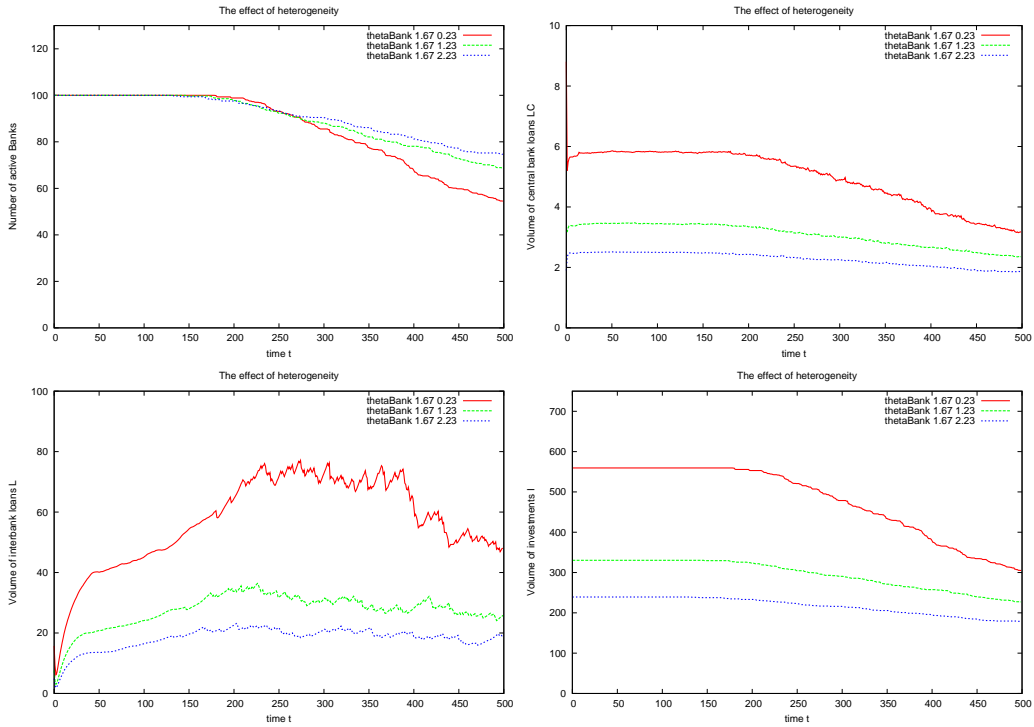
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Figure 3: The effect of heterogeneity. Top left: number of active banks over simulation time for different values of `connLevel`. Bottom left: volume of interbank loans $L$ over simulation time for different values of `connLevel`. Top right: volume of central bank loans $LC$ over simulation time for different values of `connLevel`. Bottom right: volume of investments to the real economy over simulation time for different values of `connLevel`. We have used $\rho_f^- = -0.1$ and otherwise the parameters given in section (2.3).

system leads to increasing instability. Within our model we find no confirmation of their result. This is due to the fact that heterogeneity within our model can arise only through two features. We assume that all banks face the same investment opportunities with equal risk and return profile. Banks are insofar similiar as that no bank has better screening mechanism to reduce the default probability of it's portfolio. Banks also face the same mass of depositors, which means that all banks have the same deposit fluctuations $\gamma$. In that case banks can only differ in their risk aversion parameter. The systemic stability then is not driven by the heterogeneity of the banking system, but rather by the fraction of banks that have a low risk aversion parameter. We could analyze heterogeneity in the aforementioned sense in the financial system within our model, but this is subject to a subsequent paper.
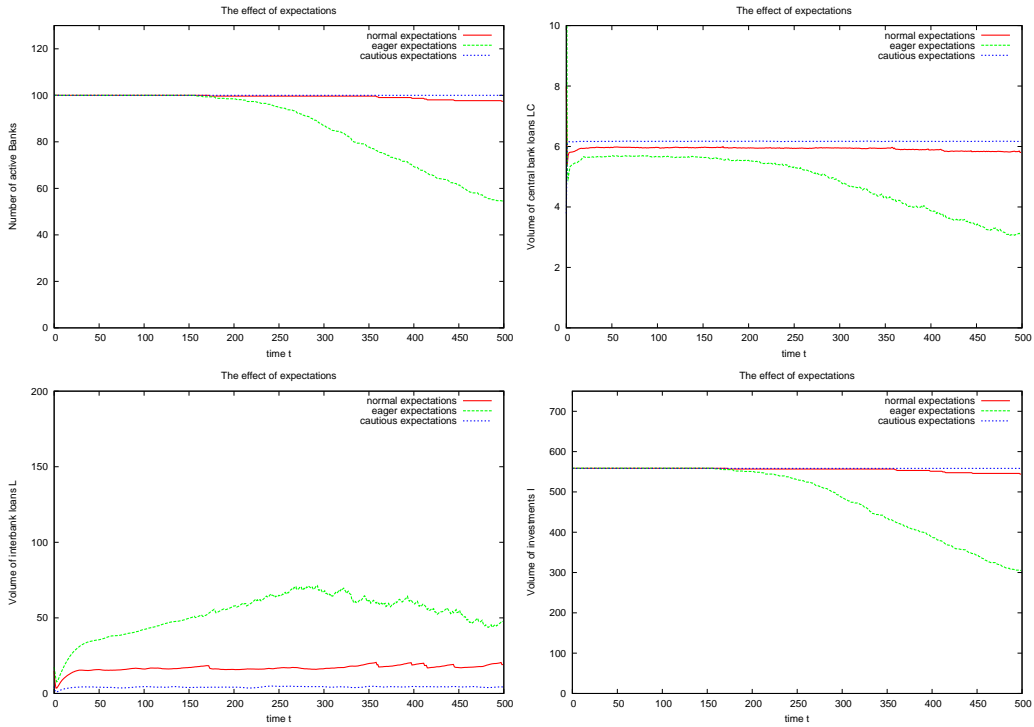
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Figure 4: The role of expectations. Top left: number of active banks over simulation time for different expectations. Bottom left: volume of interbank loans $L$ over simulation time for different expectations. Top right: volume of central bank loans $LC$ over simulation time for different expectations. Bottom right: volume of investments to the real economy over simulation time for different expectations. The parameterset for "normal expectations" are the parameters given in section (2.3). For "eager expectations" we used $p^f = 0.95$ and $\rho_f^+ = 0.07$, for "cautious expectations" we used $p^f = 0.99$ and $\rho_f^+ = 0.11$ and otherwise the parameters from section (2.3).

As we have seen in the financial crisis, it is important for banks to correctly assess the risk and return profile of their assets. Underestimating the risk profile of their assets systematically (e.g. by relying on faulty ratings) might lead to financial instability. This is analysed in figure (4) where we have shown the effect of differing values for $p^b$, $\rho_b^+$ (the bank's expected values for the success probability and return of an investment) and $p^f$, $\rho_f^+$ (the realized values). We have denoted the case $p^b = p^f$, $\rho_b^+ = \rho_f^+$ as "normal expectations". The case $p^b > p^f$, $\rho_+^b > \rho_+^f$ is denoted as "eager expectations", since banks overestimate the success probability and expected return of an

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investment. As "cautious expecations" we have denoted the case $p^b < p^f$, $\rho^b < \rho^f$ where banks underestimate the success probability and return of an investment. It can be seen from figure (4) that even a very modest systematic underestimation of the success probability and return of an investment can lead to a drastic instability. This situation corresponds to a situation where for example credit ratings are faulty and risk expectations do not correspond to real risks.

| Parameter | Influence on | | | |
|---|---|---|---|---|
| | `activeBanks` | $L$ | $LC$ | $I$ |
| $\beta \uparrow$ | $-$ | $-$ | $\uparrow$ | $-$ |
| $r^b \uparrow$ | $\downarrow$ | $-$ | $\downarrow$ | $\downarrow$ |
| $r^d \uparrow$ | $\downarrow$ | $\uparrow$ | $\downarrow$ | $\downarrow$ |
| $r \uparrow$ | $-$ | $-$ | $-$ | $-$ |
| $\gamma \uparrow$ | $\downarrow$ | $\uparrow$ | $\downarrow$ | $\downarrow$ |

Table 1: The influence of parameter variations on the number of active banks, the interbank loan level $L$, the central bank loan level $LC$ and the investment level $I$. $\uparrow$means there is a positive correlation between the parameter and the observable, $\downarrow$means there is a negative correlation and $-$ means there is no significant correlation.

There are some more parameters in the model that are of interest. One can investigate the effect of an increasing dividend level $\beta$ on financial stability, as well as the effect of an increasing required reserve rate $r$. It is also interesting to see what happens at different interest rate levels $r^b$ and $r^d$, as well as the effect of increasing deposit fluctuations (which are driven by $\gamma$). Their influence on the number of active banks, the interbank loan level, the central bank loan level and the investment level is concentrated in table (1) where we have shown how an increase in a parameter acts on the system.

One factor that determines a bank's default probability is the lumpiness of it's investments. To clarify this, assume two banks $A$ and $B$ with equal investment volume and expected return of the investment. Bank $A$ has loaned a lot of small credits, while $B$ has issued fewer, but larger credits. The success probability of a larger credit will be larger than the success probability of a small credit, as banks will audit larger credits with more scrutiny. Since the expected portfolio return $\mu_R$ of both banks should be equal and smaller
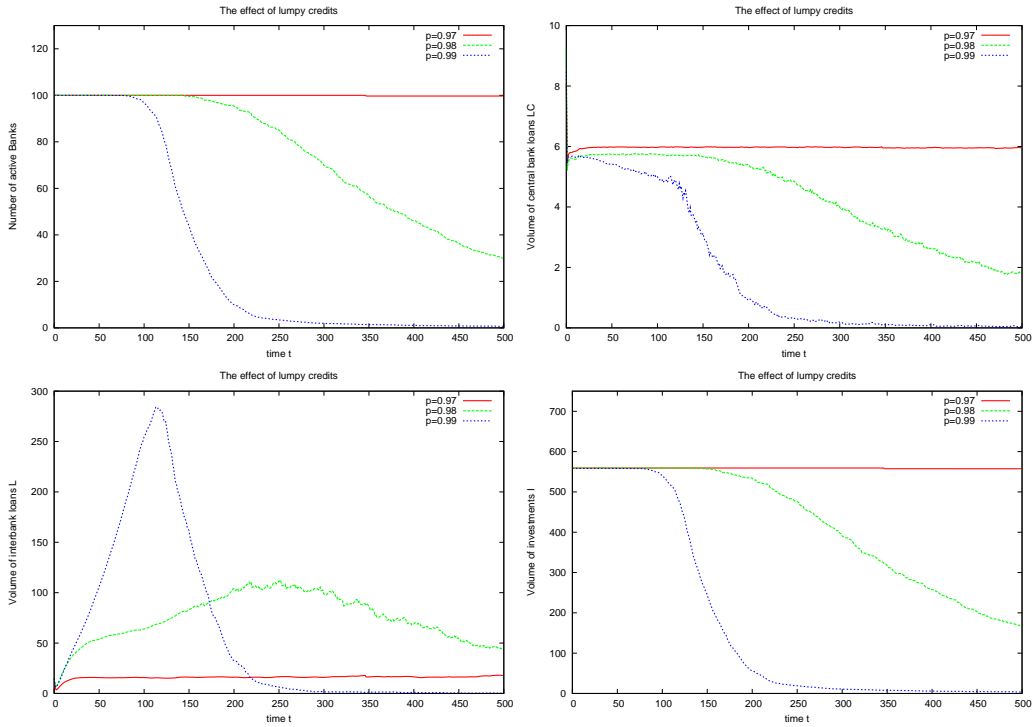
Figure 5: The effects of credit lumpiness on financial stability. Top left: number of active banks over simulation time for different expectations. Bottom left: volume of interbank loans $L$ over simulation time for different expectations. Top right: volume of central bank loans $LC$ over simulation time for different expectations. Bottom right: volume of investments to the real economy over simulation time for different expectations. We have used the parameters from section (2.3) but with different values for $p$, $\rho^+$ and $\rho^-$ as described in the text below.

credits have a lower success probability, from the equation:

$$\mu_R = p\rho^+ + (1-p)\rho^- \tag{14}$$

one can determine the "return" $\rho^-$ of a defaulting credit, if the return of a successfull credit $\rho^+$ remains the same. For $\rho_+ = 0.09$, $p = 0.97$ and $\rho_- = 0.05$ one obtains $\mu_R = 0.0858$ for small credits. We now assume a slightly larger success probability for credits of $p = 0.98$. Then one obtains with fixed $\mu_R$ a negative return $\rho^- = -0.12$. Now it is not 5% of the invested portfolio volume that defaults if an investment defaults, but 12%. This resembles the greater lumpiness of bank $B$'s portfolio. For $p = 0.99$ one obtains $\rho^- = -0.33$. Those three cases are shown in figure (5). It is clear from our
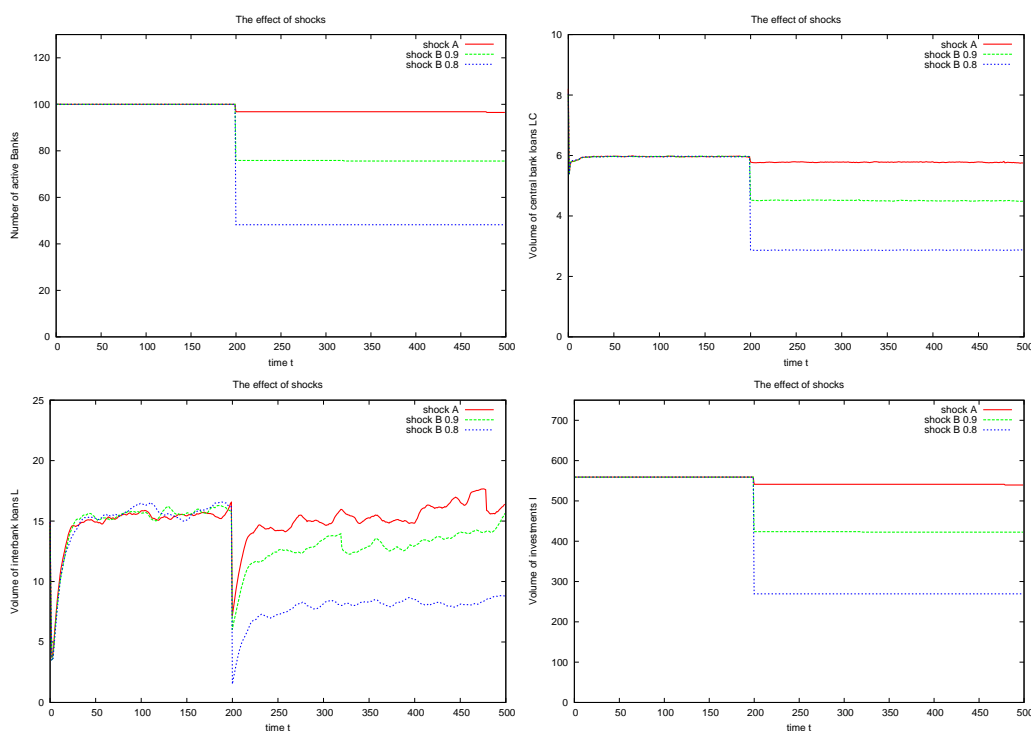
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Figure 6: The effects of different shocks to financial stability. Top left: number of active banks over simulation time for different shock types. Bottom left: volume of interbank loans $L$ over simulation time for different shock types. Top right: volume of central bank loans $LC$ over simulation time for different shock types. Bottom right: volume of investments to the real economy over simulation time for different shock types. We have used the parameters from section (2.3).

simulations, that a larger credit lumpiness leads to larger systemic instability and higher interbank loan volume.

We now want to analyse the effects of two types of shocks on systemic stability. The first shock, denoted as shock-type A, is the insolvency of a large bank. We therefore picked the bank with the largest interbank liabilities in each simulation at time $t = 200$ and reduced it's banking capital by 30% (caused e.g. by a depreciation on the asset side that has to be compensated via banking capital). The creditors of this bank now suffer losses on their asset side which leads to a reduction of their banking capital as well. This in turn might drive further banks into insolvency, even if they would have survived if it was not for the insolvency of the first bank. This is the classical

contagion mechanism on interbank markets.

The second type of shock, denoted as shock-type B, is a common shock that affects all banks in the system. Here we simulated the case where all banks have invested in the same class of assets (for example in asset backed commercial papers) and where this class of assets suffers losses, which could for example be caused by a fire-sale. We have simulated a moderate loss of 10% and 20% on the banking capital of all banks. Note that this corresponds only to small losses in all bank's investments, since banks in our model hold between 8% and 12% banking capital.

Figure (6) compares both shock types and shows that common shocks are not subordinate to contagion effects, but are indeed the greater threat to financial stability. While direct contagion effects lead to only few insolvencies, even modest common losses on bank's investments lead to a large number of bank insolvencies. Note that the number of contagious defaults is influenced by the level of interbank liquidity and that larger liquidity on the interbank market leads to more contagious defaults. The destabilizing effect of common shocks however, is in our simulations always larger than the direct contagion effect.

## 4. Conclusion and Policy Implications

In this paper we conducted a multi-agent simulation of interbank markets with household and firm sector, where the banks are agents and included the central bank into the model. We analysed which impact central bank activity has on financial stability and were able to show that the central bank has a stabilizing effect on the financial system. Our results therefore lead to the conclusion that every realistic model of the financial system should include the central bank. It is sufficient for the central bank to accept only a small fraction of the bank's assets as securities to exercise a stabilising function. We were further able to show that the liquidity provision on interbank markets has a slight positive dependency on the central bank activity, leading to the conclusion that the central bank indeed enhances liquidity allocation on interbank markets.

We also analysed which effect the interbank network structure has on financial stability and simulated different network topologies with varying

interbank connection level. Our results indicate that financial stability increases with with increasing connection level on the interbank market and that this increase is monotonous. The interbank loan volume however, does not depend monotonously on the interbank connection level: for very low connection levels there is only very little interbank lending, which increases with increasing connection level up to a certain point and then decreases again for larger connection levels. Since larger interbank lending increases the susceptibility for knock-on effects, our result indicates that the resilience to shocks depends non-monotonously on the interbank connection level.

It is an ongoing debate, whether heterogeneity in the banking system increases systemic risk. We have simulated banking systems with varying average risk aversion parameter and increasing heterogeneity. Our simulations indicate that the financial system is more stable if the average risk aversion increases. Increasing risk aversion however, decreases the investment level into the real economy (the firm sector in our model). There is therefore a trade-off between systemic stability and a high investment level. Within our model, we did not find any evidence that financial stability decreases with increasing heterogeneity of the banking sector. There is nonetheless further work required to analyse which features of heterogeneity drive financial instability.

The impact of the quality of credit ratings on financial stability is one further point of discussion. We simulated the situation where credit ratings are too optimistic by differentiating between the bank's expectations about risk and return and the true risk and return. It turns out that overly cautious expectations do not have a negative impact on systemic stability. This is in contrast with expectations that are too eager in the sense that they overestimate the expected return and underestimate the risk of an investment. Our simulations show that even small deviations from the realized values lead to large instability. This indicates that better credit ratings can enhance financial stability and reduce systemic risk.

We have also analysed the effect of credit lumpiness on systemic stability. Our simulations give evidence that systemic risk increases drastically with credit lumpiness. This indicates that financial instruments can indeed reduce systemic risk and contribute to financial stability. The current debate focusses on increasing regulation for innovative financial products and strate-

gies, while our results indicate that reduced credit lumpiness and enhanced risk sharing contribute significantly to systemic stability.

We furthermore analysed the impact of different shock-types on financial stability. We simulated the insolvency of a large bank and compared the contagion effects that are caused by this insolvency with the effects of a common shock where all banks lose a fraction of their banking capital. We find that common shocks are by no means subordinate to contagion effects, but pose instead the greater threat to systemic stability. This is in contrast with the current debate about systemic risk. In their September 2009 meeting, the G-20 explicitly address systemically important institutions, stating that "[. . .] all firms whose failure could pose a risk to financial stability must be subject to consistent, consolidated supervision and regulation with high standards" and that "[. . .] our prudential standards for systemically important institutions should be commensurate with the costs of their failure".[2] In their recent report to the G20 Finance Ministers and Governors, the Financial Stability Board (2010) explicitly addresses moral hazard arising from systemically important financial institutions and state three main objectives of an international policy reform: (i) reducing the probability and impact of failure; (ii) improving the capacity to resolve firms in crisis; and (iii) reducing interconnectedness and contagion risks by strengthening the core financial infrastructures and markets.

With their proposal, the G20 and the FSB follow a strand of literature on systemic risk that focusses on systemic risk through contagion effects. New work on systemic risk through common shocks challenges this classic view. Our model supports this challenge, even though we have modelled only a very simplified version of the financial system. Further work is required to develop more realistic models that capture all key features of the financial system in order to provide policy makers with a guideline on how to assess systemic risk.

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[2]G-20 Leaders statement, September 2009, downloadble at `http://www.pittsburghsummit.gov/mediacenter/129639.htm`.

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