Financial regulations and bank credit to the real economy

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Abstract

We present a new agent-based model focusing on the linkage between the interbank market and the real economy with a stylised central bank acting as lender of last resort. Using this model we address the tradeoff between stability and economic performance for different structures of the interbank market. We also explore the efficacy of recent regulatory reforms using our richer model. Our results suggest that the effects of regulatory leverage ratios on the banking sector's performance can vary in a complex and non-monotonic way with the state of the economy, the degree of connectivity of the interbank market and the amount of information available to market participants on bank risks.

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1. Introduction

Among the most commonly cited factors for the 2008 financial and economic crisis are the excessive leverage that banks had built up under the previous Basel guidelines and the interconnectedness of the banking system which gave it a systemic dimension. In the aftermath of the crisis, a consultative document published by the Basel Committee (2009) highlighted both these factors. The document cited, as one of the main reasons that the economic and financial crisis became so severe, the excessive on- and off-balance sheet leverage built up by the banking sector of many countries. At the same time, many banks were holding insufficient liquidity buffers to face stressed and contingency outflows in case of the evaporation of the funding sources.

The banking system therefore was not able to absorb the resulting systemic trading and credit losses nor could it cope with the re-intermediation of large off-balance sheet exposures that had built up in the shadow banking system.

The document also identified as one of the main shortcomings of the previous regulatory regime, that it placed too great a focus on idiosyncratic risk, *i.e.* micro-prudential regulation, at the expense of systemic risk, which would call for macro-prudential regulation. The post-crisis regulatory regime was therefore designed to include a significant macro-prudential component. The new proposals can be summarized as follows: ensuring that an adequate share of a bank's capital consists of 'plain vanilla' common equity, with full loss-absorbing potential; simplification and consistency in the definitions of both Tier 1 and Tier 2 capital, focusing on financial instruments which can absorb losses on a going concern basis and further international harmonisation in the definition and regulation of hybrid and innovative capital.

The new Basel 3 leverage ratio is defined as a minimum of 3% of the capital measure to the exposure measure. The capital measure consists of Tier 1 capital as defined by the risk-based capital framework. The exposure measure is defined as the sum of the following exposures: (i) on-balance sheet exposures; (ii) derivative exposures; (iii) securities financing transaction exposures; and (iv) off-balance sheet items. One of the impacts of this new approach is that it considerably widens the definition of what constitutes leverage in the banking system. Thus even without altering the statutory leverage ratios, it would have considerably increased the burden on banks to either increase their capital or reduce their intermediation activity.

Critics of the new capital requirement, such as Beltratti and Stulz (2012) argue that banks that experienced the strongest decrease in market value were not correlated with those that had the highest leverage ratio and that it represents a sharp deviation from capital adequacy rules calibrated to risk weighted assets. Blum (2007), on the other hand, claims that the new regulation will reduce banks' incentives to understate their true risks, while Haldane and Madouros (2012) empirically support the thesis that the new leverage ratio appears to have greater pre-crisis predictive power than risk-weighted alternatives.

Critics of the new regulations also point to the fact that it is going to push banks towards issuing more equity which is a costlier form of financing than debt since equity holders require higher returns than debt holders. Cecchetti (2010) counter-argues that banks could meet the new rules by a combination of retaining more of their earnings, decreasing remuneration rates on debt liabilities and reducing overhead costs including managerial compensation. In addition, if the reforms make the banking system safer, the cost of raising equity will correspondingly fall. Since many of these effects are likely to take place over a longer term, whether or not they occur while depend on whether in the short run, obliging banks to reduce their leverage ratio will increase systemic safety more than it reduces the intermediating role of the banking system. If that occurs, it will be more likely that the system will move into a long term equilibrium with greater stability and no sacrifice in efficiency.

The aim of this paper is to study this question, using an agent-based model of the banking sector coupled to a simplified real sector. Our model of the banking sector has been developed as part of a longer-term project on creating an agent-based model with endogenous determination of both the real macro-economy and the financial sector. In our model, the real economy is treated as a black box that demands funds from financial intermediaries, produces surpluses which sustain profitability and generates risk that underlies both the riskiness of the banking system. This creates a basis for endogenising banks' choices on how much and where to invest their available funds and which sources to obtain funds from (equity is considered fixed in the present model). The model is used to address the tradeoff between stability and efficiency of the banking system.

The context in which this tradeoff is studied needs to be clarified: ours is not a model of black swan events, *i.e.* large-scale bubbles and crashes, rather it is one in which both real sector lending and interbank lending fluctuate in on ongoing fashion due to defaults arising both from the real sector and within the interbank market. Stability in our model is measured via the rate at which banks default while efficiency is measured by the volume of funds intermediated to the real sector as well as by the aggregate profits generated within the banking and real sector.

A number of agent-based models have considered the interrelation between the credit market and the real economy and the possibly de-stabilising role of feedback loops between the two systems (Grilli *et. al.* (2014), Tedeschi *et. al.* (2012), Battiston *et. al.* (2012), DelliGatti *et. al.* (2009)). However, in these models the emphasis is on the behaviour of firms and households, with banks providing credit following somewhat unrealistic rules of thumbs. In our model we take the opposite approach. We provide an agent-based micro-foundation to the strategies of banks while simplifying the role of households and firms, whose behaviour is captured by stochastic processes for deposit fluctuations and demand for loans.

The model builds on Iori *et. al.* (2006) by endogenising (1) the allocation of a bank's funds between firm-loans, inter-bank loans, and cash reserves; (2) counter-party rating schemes and interest adjustment models; (3) lending as dependent on counter-party credit risk; (4) learning and strategic behaviour of banks; (5) banks decision rules are made contingent on leverage requirements and interbank exposure.

We use the model to study the comparative static effects of regulatory requirements, connectivity between banks and the relative size of the real to the financial sector. We also use the model to study the impact of recent reforms to regulatory policy: namely, the Pillar 3 rules of Basel 2 that require the disclosure of information related to bank risk and counter-cyclical capital buffers as proposed under Basel 3.

The results of our model provide some support, albeit qualified, to the concerns raised by critics of the recent tightening of regulatory capital requirements under the new Basel framework. While permanently low ceilings on leverage ratios can protect banks from idiosyncratic as well as systemic risk, they do have an anti-competitive effect which hurts borrowers in the real economy, especially in times when the demand for bank credit is high. At the same time, while dynamically counter-cyclical leverage ceilings can reduce the rate of bank defaults, these too discourage the average level of financial intermediation to the real sector over the course of a business cycle.

Other results include the possibility that greater bank connectivity, which proxies for the removal of financial frictions, can have a non-monotonic effect on bank stability, first increasing the risk of contagion and then decreasing it. Finally, aggregate profitability of banks and firms, our proxy for the economic performance of the system, can also have am ambiguous relationship with both connectivity and regulatory leverage. There thus appears to be no "one-size-fits-all" solution to financial regulation as both the intermediation role and the stability of banks vary in relation to demand conditions, the structure of the interbank market and regulatory settings.

The rest of the paper is structured as follows. Section 2 covers related literature; Section 3 describes the model; Section 4 presents results from baseline simulations meant to ensure that the model produces sensible results. Section 5 discusses the effects of regulatory ceilings on the allocations of bank funds, interest rates on various kinds of loans, profitability of banks and firms and the stability of the banking system. Section 6 analyses the effects of recent regulatory reforms: disclosure of bank risks and counter-cyclical variation in leverage requirements. Section 7 concludes and draws policy implications.

2. Literature Review

The literature on systemic risk in credit markets has developed in several dimensions. Some authors have analysed the relationship between the network structure of the interbank market and its resilience to different kind of shocks (Iori *et. al.* (2006); Battiston *et. al.* (2012); Lenzu and Tedeschi (2012); Georg (2013); Gai *et. al.* (2011)). Others have focused on the effects of asset fire-sales, roll-overs of risk and portfolio overlaps (Nier *et. al.* (2007), Caccioli *et. al.* (2012a); Anand *et. al.* (2012)) as sources of contagion. A few studies have considered possible feedback loops between the macro-economy and the financial sector (Lenzu and Tedeschi (2012), Tedeschi *et. al.* (2012), Battiston *et. al.* (2012), DelliGatti *et. al.* (2009)).

Broadly, two different approaches have been adopted. One approach assumes the network of exposure among market participants as given, possibly calibrated to real market data. Stress scenarios are simulated by applying idiosyncratic, or system-wide shocks, and their effects are monitored in the parameter space. The second approach assigns behavioural rules, either *ad hoc* or micro-founded, to economic agents and organisations. Balance sheet and reciprocal exposures are endogenously determined by the portfolio allocation strategies. Defaults events are endogenously generated in this context, even if the dynamics of the system are driven by exogenous risk factors.

Gai and Kapadia (2010) is an influential example of the first approach. The authors explore how the probability and potential impact of contagion is influenced by aggregate and idiosyncratic shocks, changes in network structure, and asset-market liquidity. The authors show, via impulse response exercises, that the interbank market presents a robust-yet-fragile property: while the probability of contagion might be low, its effects can be extremely widespread if it occurs.

Caccioli *et. al.* (2012a) extend the model of Gai and Kapadia (2010) to account for a number of empirically observed properties of financial networks, namely heterogeneous degree distributions, heterogeneous asset distributions and degree correlation among connected banks. In their model an heterogeneous distribution of assets increases the probability of contagion even with respect to random failures. An increase of the capital buffer of a few big banks can significantly reduce the contagion probability of highly connected networks. A policy targeted to increase the capital buffer of the most connected bank is ineffective. Correlations, depending on their direction, can either increase or decrease the probability of contagion. Networks with heterogeneous degree distributions are more resilient to contagion triggered by the random failure of a single bank, but more vulnerable to contagion triggered by the failure of highly connected bank nodes.

Caccioli *et. al.* (2012b) analyse a model of financial contagion driven by common asset holdings. The relevant parameters for the model are the average diversification (the average number of assets held by banks) and the initial leverage of banks. Contagion occurrences are non-monotonic in the diversification parameter while increasing leverage increases the overall instability of the system, and there is a critical level of leverage below which global cascades do not occur for any value of diversification or crowding. Anand *et. al.* (2012) analyse how the role of macroeconomic fluctuations, asset market liquidity and network structure in determining contagion and aggregate losses in a stylised financial system. Calibrating the model using publicly available data from advanced-country banking sectors, they illustrate how macroeconomic fluctuations and asset price feedback effects intertwine to generate fat tailed distributions of bank losses and make large-scale financial disruption possible.

Iori *et. al.* (2006) introduce one of the first agent-based models of contagion via interbank lending within a dynamical framework that leads to endogenously generated interbank exposures. In the model banks face risk free, but random, investment opportunities and exchange reserves in the overnight interbank to counteract exogenous deposit fluctuations and to satisfy their reserve requirements. The paper highlights the importance of heterogeneity in explaining the effects of interbank linkages on systemic risk. With homogeneous banks, an interbank market unambiguously stabilises the system; with heterogeneity, knock-on effects become possible. The stabilising role of interbank lending remains in the sense that idiosyncratic banks defaults become less likely, but when they occur their systemic impact is stronger, echoing the robust-yet-fragile property also found in Gai and Kapadia (2010).

Moreover the authors distinguish between direct or indirect contagion. A direct effect arises via knock-on from a failing bank to its direct creditors. An indirect effect arises when, following the defaults of one or several banks, the interbank market's liquidity is depleted, reducing the opportunities for banks that need additional interbank funding. The model shows that indirect effects are much more important than the direct ones. The indirect contagion effect provides an alternative explanation to the credit crunch aspect of the liquidity hoarding hypothesis.

Ladley (2013) extends the model of Iori *et. al.* (2006) in a partial equilibrium setting in which banks' portfolios and the interbank interest rate are determined endogenously. The paper investigates the effects of the market connectivity structure on contagion, under both individual and systemic shocks, and assesses a number of mechanisms for mitigating the impact of systemic risk. When shocks are economy-wide, interbank linkages spread systemic instability. On the contrary when shocks are limited, interbank linkages improve the stability of the system. The effect of interbank linkages on systemic stability thus varies with the nature of the shock and there is no optimal network structure resistant to all kind of shocks.

Georg (2013) considers an interbank market that includes both commercial banks and a central bank. Commercial banks optimise their portfolios between risky investments and riskless reserves. Banks are subject to two sources of uncertainty: fluctuating deposits and risky investments. Illiquid banks can borrow both on an un-collateralized interbank market and through collateralized central bank loans. The paper shows that the interbank network structure plays little role in systemic stability during normal times, while it becomes crucial during periods of financial distress (captured by a higher volatility of deposit fluctuations and returns on investments). During a crisis period, networks with large average path length are more resilient to financial distress. Central bank intervention can alleviate financial distress in the short run. However if the central banks accepts a large proportion of bank assets as collateral, it causes a crowding-out effect reducing volumes on the interbank market.

3. The Model

The economy consists of four types of players: commercial banks (or simply banks), firms, households and a Central Bank. Households are the source of bank deposits and firms are the primary recipient of loans. The aggregate supply of deposits from households to banks is assumed to be constant and is redistributed each period amongst existing banks by means of an exogenously specified zero-sum stochastic process. Firms post demands for loans from banks and this too follows a random process. Each firm has a fixed and exogenous probability of default on loans. The Central Bank stands ready to supply liquidity as needed by banks as well as to accept excess reserves from banks at rates that it sets. These rates also establish the corridor between which bank lending to firms and to each other takes place. Figure 1 below describes the system.

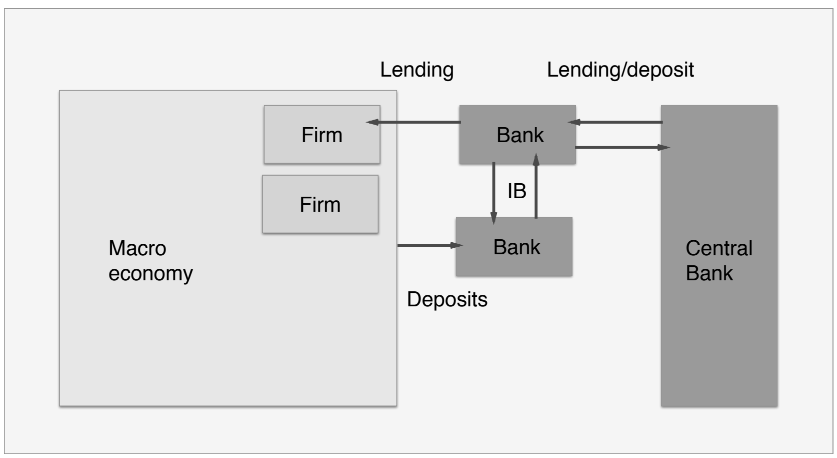

Figure 1: A schematic overview of the economy.

3.1. Balance sheets

There are N_B commercial banks, N_F firms and one Central Bank. The assets of commercial bank j are defined as:

$$\begin{aligned}
\mathcal{A}_j(t) &= R_j(t) + L_j(t) \\
L_j(t) &= L_j^f(t) + L_j^b(t), \\
L_j^f(t) &= \sum_{i=1}^{N_F} L_{ji}^f(t) \\
L_j^b(t) &= \sum_{k=1}^{N_B} I_{jk}^{\ell}(t)
\end{aligned}$$

where $R_j(t)$ are cash reserves, if any, held by bank j with the central bank at time t $L_{j,i}^f(t)$ is the book value at time t of a loan extended from bank j to firm i, and $I_{jk}^{\ell}(t)$ is the book value at time t of a loan extended from bank j to bank k ($I_{jj}^{\ell}(t) = 0$).

The liability side of the bank's balance sheet is given by:

$$\mathcal{L}_j(t) = D_j(t) + \sum_{k=1}^{N_B} I_{jk}^b(t) + C_j(t),$$

where $\mathcal{L}_j(t)$ represents the liabilities of bank j at time t; $D_j(t)$ is the value of household deposits held by bank j, $I_{jk}^b(t)$ is the book value at time t of a loan extended from bank k to bank j and $C_j(t)$ is the value of any funds borrowed from the Central Bank at time t. $R_j(t)$ and $C_j(t)$ are both net figures. In other words, in any period t, either $R_j(t) \geq 0$ and $C_j(t) = 0$ or $C_j(t) \geq 0$ and $R_j(t) = 0$.

By definition the equity of the bank is:

$$\mathcal{E}_j(t) = \mathcal{A}_j(t) - \mathcal{L}_j(t),$$

Banks choose a leverage ratio λ that determines the proportion of loans to equity in their portfolio $\hat{L}_j(t) = \lambda_j \mathcal{E}_j(t)$. This ratio cannot exceed the maximum leverage ratio allowed by regulators, but it might be less than that.[1] We assume, for simplicity, that if banks wish to increase leverage

[1]We assign equal weight to all loans in calculating the leverage ratio for regulatory compliance. We abstract from the risk-weighted calculations because our simulations are designed to generate qualitative insights into the causal relationship between regulatory measures and bank performance and not for quantitative policy simulations.

(without violating the regulatory constraint) they can always find funds by making use of the Central Bank window although the costs of these funds will be normally higher than borrowing from other banks.

3.2. Beginning of day regulatory check

At the beginning of the trading day bank j pays interest at the constant and exogenous rate r^D to depositors, repays its interbank loans (if any) at the rate $r^b_{jk}(t-1)$, loans from the Central Bank (if positive) at the constant and exogenous rate r^H, receives repayment on loans from each borrowing firm i at the rate $r^f_{ji}(t-1)$ (unless firm i defaults) and each borrowing bank k at the rate $r^\ell_{jk}(t-1)$ (unless bank k defaults), and receives interest on the cash deposited (if positive) in its central bank account at the rate r^L.[2]

Bank's equity is adjusted as follow

$$\mathcal{E}_j(t) = \mathcal{E}_j(t-1) + d\mathcal{E}_j(t)$$

where

$$\begin{aligned} d\mathcal{E}_j(t) &= R_j(t-1)(1+r^L) \times I - C_j(t-1)(1+r^H) \times (1-I) \\ &\quad + \sum_{i=1}^{N_F} L^f_{ji}(t-1)(1+r^f_{j,i}(t-1)) + \sum_{k=1}^{N_B} I^\ell_{jk}(t-1)(1+r^\ell_{jk}(t-1)) \\ &\quad - \sum_{k=1}^{N_B} I^b_{jk}(t-1)(1+r^b_{jk}(t-1)) - D_j(t-1)(1+r^D). \end{aligned}$$

where I is an indicator function which takes on the value 1 if $R_j(t-1) > 0$, $C_j(t-1) = 0$ and 0 if $R_j(t-1) = 0$, $C_j(t-1) > 0$. If bank equity becomes negative at this point the bank goes into default.

3.3. Lending to firms

Banks receive demands for loans from firms. Firms can only borrow from banks with which they share a connection. Lending to firms is the main source of both reward and risk to the banking system. Reward, because firms are able to exploit investment opportunities that provide real returns

[2]For the purposes of simulations we set $r^D = 0$. This is because the household sector is treated more or less exogenously in the present paper.

to the economy and risk, because these opportunities are idiosyncratically risky and might lead the firm to default on its loan.

The probability that a firm defaults is ρ which is exogenous, identical across firms and known to banks. The demand size is random, distributed according to $\Gamma(2, \bar{d}/2)$, where $\bar{d}$ is the average demand for loans. This was chosen to generate heterogeneity in banks' exposures to firms. Loans to firms are for one period. For simplicity we assume that firms either repay the loan in full (principal plus interest) or do not pay at all (default). Firms have a stepwise demand function in each period. They will borrow all of their demand at any rate up to a maximum threshold, which differs across firms, but once the rate is above their threshold they borrow nothing.[3]

The lending rate to firms is updated so to try and achieve the target leverage level. Thus, as will be elaborated in Section 3.8.2, if a bank has not been able to lend all its desired level to firms it reduces the lending rate; otherwise it increases it. The rate is bounded from below by the bank's marginal funding cost $c_j(t)$ per unit of funds. $c_j(t)$ varies with the source of funding as will be explained below.

The reservation (lowest) price at which bank j is willing to lend to firm i, given its risk of default is described by the condition

$$(1 + \underline{r}^f_{ji}(t))(1 - \rho) + \gamma\rho \geq (1 + c_j(t)) \quad \forall j, \tag{1}$$

where $\underline{r}^f_{ji}(t)$ is the minimum rate at which bank j will lend to firm i and γ is the recovery rate in case of default. Although included in equation (1) for completeness' sake, in our actual simulations γ was set at zero, so we shall henceforth drop it. Thus the reservation price on firm lending is given by

$$\underline{r}^f_{ji}(t) = \frac{1 + c_j(t)}{1 - \rho} - 1. \tag{2}$$

The above condition states that a bank will not lend to a firm at an interest rate which lies below its expected cost of funds $c_j(t)$. $c_j(t)$ is in turn a weighted average of interest rates paid by the bank on previous borrowing,

[3]Threshold heterogeneity leads to an aggregate downward sloping demand curve. One way to justify this is to assume that firms are perfectly competitive, risk-neutral profit maximisers that receive idiosyncratic investment opportunities i that pay $\Pi_i > 0$ with probability $1 - \rho$ and 0 with probability ρ. The maximum interest rate that firm i would then be willing to pay would be the one that makes it break even in expectation.

where the weights represent the different sources of funds.

$$c_j(t) = \omega_j^D(t) r^D + \omega_j^b(t) E[r_j^b(t)] + \omega_j^C(t) r^H \tag{3}$$

where $E[r_j^b(t)]$ is the expected cost of borrowing on the interbank market, given by

$$E[r_j^b(t)] = \sum_{\tau=1}^{T^b} r_j^b(t-\tau) \frac{I_j^b(t-\tau)}{\sum_{\tau=1}^{T^b} I_j^b(t-\tau)} \tag{4}$$

which is the weighted average of past borrowing from the interbank market by bank j with T^b being the length of memory of past rates. If in some period $t-\tau$ the bank did not borrow then $r_j^b(t-\tau) = 0$. $\omega_j^i(t)$ are the respective shares of source i in bank j's total financing $(i = D, I^b, C))$ in recent history immediately preceding time t, r^D and r^H are known constants.

Note that the minimum rate for lending to firms depends only on the bank's characteristics, namely its average cost of funds, and not on those of the borrowing firm. This is because firms are identical in their default probabilities. We therefore define the threshold interest rate as $\underline{r}_j^f(t)$, dropping the firm subscript i for this variable.

Note that the bank may not achieve the desired level of lending to firms. $L_j^f(t)$ represents the actual amount of loans to firms provided by banks j at time t.

3.4. Shocks to deposits

After banks have committed to lend to firms they receive a pair of exogenous shocks to their deposits. To begin with, each bank j faces a uniform probability that between zero and 10 percent of its previous deposits will be withdrawn. Thus the amount

$$\Omega_j(t) = d_j(t) \times D_j(t-1)$$

is withdrawn from bank j, where d_j is drawn from $U[0, 0.1]$. Then, the aggregate amount withdrawn is redeposited into the banking system, with each bank receiving a share that is proportional to its relative equity:

$$\Lambda_j(t) = \frac{\mathcal{E}_j(t)}{\sum_{k=1}^{N_B} \mathcal{E}_k(t)} \sum_{k=1}^{N_B} \Omega_k(t)$$

Thus, deposits at the start of $t+1$ will be updated by

$$D_j(t) = \Lambda_j(t) - \Omega_j(t) + D_j(t-1) = \Lambda_j(t) + (1 - d_j(t))D_j(t-1)$$

We assume that withdrawals from and fresh deposits into each bank take place simultaneously.[4]

At the end of this cycle, banks compare their available liquidity against their liquidity needs and enter the interbank market as potential borrowers or potential lenders depending on whether the latter exceed the former or fall short of it.

The former consist of starting reserves $R_j(t)$ plus the excess of fresh deposits over withdrawals (if positive); while the latter consists of loan commitments to firms $L_j^f(t)$ plus the excess of withdrawals over fresh deposits (if positive). The following equation captures the balance of liquidity at this stage:

$$I_j(t) = R_j(t) + \Lambda_j(t) - \Omega_j(t) - L_j^f(t)$$

If $I_j(t) > 0$ then bank j enters the interbank market as a potential lender with a supply $I_j^\ell(t) = I_j(t)$ in loans while if $I_j(t) < 0$, it enters as a borrower with a loan demand of $I_j^b(t) = -I_j(t)$.[5]

3.5. The interbank market

In case banks end up with negative positions on their central bank accounts after the shock, they enter the interbank market as borrowers while banks with positive accounts enter as lenders. We assume that interbank lending is restricted to an exogenous pre-determined network (to mimic OTC lending). This is done via a fixed (for each simulation) Erdos-Renyi random graph, which allows us to go from the extreme of an anonymous fully connected market to a very weakly connected market.[6]

[4]This assumption allows us to simplify the computation of liquidity needs: essentially a bank meets all (net) withdrawals by an intra-day overdraft on its account with the Central Bank without incurring a financial or reputational cost, but the account must be brought back into balance at the end of the day.

[5]The above formulation assumes that mandatory reserve requirements are set at zero. This rules out the possibility of liquidity constraints acting as barriers to interbank lending. Iori *et. al.* (2006) have shown the potential for of reserve requirements to reduce the liquidity and hinder the risk-sharing role of interbank markets with ex ante homogenous banks.

[6]A random graph is obtained by starting with a set of n isolated vertices and adding successive edges between them at random. In the Erdos-Renyi model each edge is equally

Lending on the interbank market does not bear liquidity risk and banks are willing to lend all their excess cash, as long as they can make an expected profit (accounting for the risk of default of borrowers) at least comparable to leaving reserves with the Central Bank.

Borrowing banks bid for loans by offering rates to lending banks which are in turn constrained by the central bank lending rate. All loans are overnight. As will be made precise in Section 3.8.3, the offer rate is updated by an adjustment mechanism which depends on their success in borrowing in the last period in which they attempted to borrow: banks that were unsuccessful increase the rate offered and those that were successful, decrease it.

Lenders' reservation rates are determined by the condition

$$(1 + \underline{r}^{\ell}_{jk}(t))(1 - p^b_k(t)) = 1 + r^L \quad \forall jk \tag{5}$$

where p^b_k is the probability that bank k defaults.[7] Thus

$$\underline{r}^{\ell}_{jk}(t) = \frac{1 + r^L}{1 - p^b_k(t)} - 1 \tag{6}$$

Note that each lender's reservation rate for lending to borrower k will be identical, depending only on the Central Bank deposit rate r^l and the borrower's default probability, $p^b_k(t)$. Thus, we can denote $\underline{r}^{\ell}_k(t)$ as the reservation rate that all lenders will be willing to lend to borrower k at.

Borrowers compete for liquidity and they post bids at the rate

$$r^b_k(t) = \underline{r}^{\ell}_k(t) + \tilde{r}^b_k(t) \tag{7}$$

where $r^b_k(t)$ is the rate offered by borrower k to any lender and this includes $\tilde{r}^b_k(t) \geq 0$, which is a mark-up that borrower k offers over a lender's reservation rate.

likely to occur. Each edge is included in the graph with a probability that is independent from every other edge. An Erdos-Renyi graph does not have heavy tails, and has low clustering. In this sense it may appear an inappropriate choice for modelling interbank lending. Nonetheless the Erdos-Renyi graph only models the network of crudity lines (allowed transactions) and not the network of realised interbank loans.

[7]If the recovery rate after default was equal to a positive constant, γ, the equivalent condition would be

$$(1 + \underline{r}^{\ell}_{jk}(t))(1 - p^b_k(t)) + \gamma p^b_k = 1 + r^L$$

Borrowers post their bids and lenders, in random order, observe their neighbouring borrowers' bids, compute the profitability of each bid as

$$\pi_{jk}(t) = [r_k^b(t) - r_k^\ell(t)] \tag{8}$$

and then fill them in order of profitability.

3.6. Central Bank

Failing to borrow all they need from the interbank market, solvent but illiquid banks can borrow from the Central Bank. We assume that the Central Bank accepts loans to firms as collateral without charging a haircut. Thus a solvent bank's liquidity needs will always be satisfied by the Central Bank. For a more realistic version of the model, it would be important to model funding constraints explicitly, for example as done in Georg (2013).

Banks with excess liquidity earn interest r^L on the Central Bank's account, while banks that borrow liquidity from the Central Bank pay $r^H > r^L$. Accounts held at the Central Bank are the least lucrative asset while borrowing from the Central Bank is the most expensive liability. Thus the Central Bank interest rates frame all other interest rates in the system.[8] In addition, borrowing from the Central Bank facility carries a stigma effect which makes it more difficult for the bank to borrow on the interbank market in future periods. As is elaborated on the following sub-section, the stigma leads to banks being denied interbank funds for a fixed number of subsequent periods.

3.7. Bank defaults

We assume two different scenarios to estimate the probability of default by banks. In the first, we assume that banks cannot estimate each other's default probability and lending banks start with a uniform prior over all borrowing banks, which is equal to the historical average rate of default in the interbank market over the past T^h periods. But if a bank goes to the Central Bank to seek funds, its borrowing is observed by other participants who then update their prior about that bank and deny it loans over a fixed

[8] This is true for the normal functioning of a financial system. In times of acute crisis, Central Banks might lend at below market interest rates to prevent liquidity from drying up, as happened in the aftermath of the 2008 crisis. In this paper, we do not consider the active monetary policy as a stabilising tool, since our focus is on macro-prudential regulation via leverage constraints. Thus we have chosen a scenario which reflects Central Bank interest rates in normal times.

number of future periods, T^g. In practice in our simulations both T^h and T^g are set at one period each.

In the second scenario, we assume that each bank's probability of default can be computed by all other banks on the basis of common knowledge of its risk characteristics. This scenario reflects the third pillar of the Basel 2 accords: market discipline which calls upon banks to make full disclosure of their risk characteristics to market participants.

In practice we make two simplifying assumptions in computing default probability in this scenario. First that given the amount of loans committed by a bank to firms and given its equity, its probability of default is derived from the probably of defaults by its debtor firms (i.e. probability that losses on firm lending exceed equity). In this sense, banks ignore contagion effects on each other's defaults and only concentrate on 'fundamental sources of default. Second, we use a normal approximation to the binomial distribution of losses which assumes that each bank-firm loan is of equal size, has the same probability of default, and the defaults are independent. This is consistent with the Basel approach to estimating default probability.[9]

The probability of default by bank k with loans to $N_k^f(t)$ firms is

$$p_k^b(t) = P\left(N_k^\delta(t) L^f > \mathcal{E}_k(t)\right) \tag{9}$$

where L^f is the standardised size of a loan and N_k^δ are the number of bank k's non-performing loans ($N_k^\delta(t) < N_k^f(t)$).

Although the second scenario reflects a regulatory goal, compliance with it has been slow and uneven as the 2007-2008 crisis demonstrated. Sowerbutts *et. al.* (2013) cite inadequate disclosure, both in terms of levels of information made public and in terms of its relevance for accurate assessment of bank risks as significant contributing factors to the crisis. Thus we shall use the first scenario which reflects a more accurate picture of the status quo as our benchmark one and the second scenario as the policy-induced variant. The first scenario will accordingly be referred to as the Benchmark (or Model B) and the second one as the Disclosure (or Model D) variant.

In both cases, should a bank default, its available funds are distributed first to depositors, then to pay back Central Bank loans if any, and finally to pay whatever is left over to its interbank creditors in proportion to their

[9]In the case of correlated defaults, one could use the one factor Vasicek model used to calculate the Internal Ratings-Based (IRB) approach of Basel II.

loans. In order to keep the number of banks constant, we assume that for each defaulting bank, a new bank is created by the regulator whose initial size is a fraction of the initial size of the original banks. The resources to set up the new bank are raised by a proportionate tax on the equity of existing banks. In this way the banking system as a whole suffers a loss beyond the unpaid debts of the defaulting back. This mechanism also reflects some of the new proposals for the resolution of bank failures to make minimal use of public funds.[10]

3.8. Learning

For rate bidding behaviour in the real sector or on the interbank market, we assume that banks use simple threshold adjustment mechanisms in order to achieve desired targets. If they have been successful in bidding in the most recent period in which they made a bid, *i.e.* they were able to achieve or come close to achieving their target, they decrease the competitiveness of their offer in the current period and try to extract a bigger surplus, whereas if they have been unsuccessful they make their offer more competitive. Rates are further constrained by the rates on borrowing from the Central Bank or on placing deposits with it.

The main target of banks is a desired leverage ratio which they choose to maximise profitability while remaining compliant with regulatory leverage ratios. We first describe how this ratio is chosen and how it is periodically updated.

3.8.1. Leverage target

Banks start the initial period by randomly choosing a leverage target $\tilde{\lambda}_j(0)$ from an interval $\tilde{\lambda}_j \in [\tilde{\lambda}, \tilde{\lambda}(1+\Delta_\lambda), \tilde{\lambda}(1+2\Delta_\lambda), \cdots, \tilde{\lambda}(1+M\Delta_\lambda)]$, where Δ_λ is a fixed increment to the leverage target and M represents the maximum number of increments allowed by regulatory constraints. Once a target is chosen, banks direct their bidding behaviour to achieve it until a

[10]In particular, the Directive on Bank Recovery and Resolution determines the rules for how EU banks in difficulty are restructured, how vital functions for the real economy are maintained, and how losses and costs are allocated to the banks shareholders and creditors. Being aimed at minimising the impact on public deficits, the framework is based on the involvement of bank market participants in a common resolution plan and a joint deposit insurance scheme to strengthen the integrity of the financial system and reduce systemic risk.

fixed number of periods, denoted by T^λ, have expired at which time they choose a new target from the discrete set.

During the interval of time before a target is updated each bank keeps assessing the relative profitability of the leverage levels that are actually achieved. This information helps the bank choose a new target when the time for that comes.

Thus, suppose that at some time t a bank j has a fixed leverage target which it is trying to meet via its bidding behaviour. At the beginning of that period (barring default) bank j looks at the leverage actually achieved in the previous period, $\lambda_j(t-1)$ and rounds this to the closest possible leverage target $\tilde{\lambda}(1+i\Delta_\lambda)$ where i is the point in the range of discrete targets that comes closest to $\lambda_j(t-1)$. Note that $\tilde{\lambda}(1+i\Delta_\lambda)$ is not necessarily equal to its actual target at time t. But given that $\tilde{\lambda}(1+i\Delta_\lambda)$ comes close to what was actually achieved, bank j will evaluate its relative profitability by treating it as a quasi-target for the coming period, denoting it by $\hat{\lambda}_j(t)$ and computing

$$\Pi(\hat{\lambda}_j(t)) = \Pi(\hat{\lambda}_j(t-1))e^{-\delta} + R_j(t-1)(1+r^L)\times I - C_j(t-1)(1+r^H)\times(1-I) +$$
$$\sum_{i=1}^{N_F} L^f_{j,i}(t-1)(1+r^f_{j,i}(t-1)) + \sum_{i=1}^{N_B} I^\ell_{jk}(t-1)(1+r^\ell_{jk}(t-1))$$
$$-\sum_{h=1}^{N_B} I^b_{h,j}(t-1)(1+r^b_{h,j}(t-1)) - D_j(t-1)(1+r^D).$$

where Π is profits and δ is a memory decay rate. Thus the profitability of a quasi-target $\hat{\lambda}_j(t) = \tilde{\lambda}(1+i\Delta_\lambda) \approx \lambda_j(t-1)$ is the discounted value of profits of its analog in the last period plus the flow of net profits that resulted from it in the last period.

This allows the bank to keep a memory of the profitability of attained leverage. After each interval κ of T^λ periods, $\kappa = T^\lambda, 2T^\lambda, 3T^\lambda\cdots$, the bank will select a new leverage ratio $\tilde{\lambda}(1+m\Delta_\lambda)$ with probability

$$p(\tilde{\lambda}(1+m\Delta_\lambda)) = \frac{e^{\beta\Pi(\tilde{\lambda}(1+m\Delta_\lambda)}}{\sum_{i=0}^{M} e^{\beta\Pi(\tilde{\lambda}(1+i\Delta_\lambda)}} \tag{10}$$

In other words, the new target is selected randomly but with a probability that increases in its relative profitability, as calculated in each period over which the above computation was carried out.

3.8.2. Bank rates to firms

Given a leverage target that is held fixed over T^{λ} periods, a bank will prioritise lending to firms over lending to other banks or placing reserves with the Central Bank. This is both because of the timing of events within a day and because firm loans will generally be more lucrative. Thus its loan target to firms will equal its leverage target.[11] We now explain how bank j adjusts its ask rate from firms in order to achieve its given loan target.

Suppose that the bank has set a loan target $\tilde{L}^f(\kappa)$, $\kappa = T^{\lambda}, 2T^{\lambda}, 3T^{\lambda} \ldots$. Let $t-1$, t be periods of time that both occur while the target is held fixed. Recall that bank j's ask rate at time t can be expressed as

$$r_j^f(t) = \underline{r}_j^f(t) + \tilde{r}_j^f(t) \tag{11}$$

where $\underline{r}_j^f(t)$ is the break-even rate for lending to firms, as defined in equation 2, and $\tilde{r}_j^f(t) \geq 0$ is bank j's desired mark-up over the break even rate. The latter will be updated at time t as follows

$$\begin{aligned}
\tilde{r}_j^f(t) &= \tilde{r}_j^f(t-1) - \Delta_{\tilde{r}^f} \times U(0,1) \text{ if } L_j^f(t-1) < \eta_0^f \tilde{L}_j^f(\kappa) \\
\tilde{r}_j^f(t) &= \tilde{r}_j^f(t-1) \text{ if } L_j^f(t-1) \in (\eta_0^f \tilde{L}_j^f(t-1), \eta_1^f \tilde{L}_j^f(\kappa)) \\
\tilde{r}_j^f(t) &= \tilde{r}_j^f(t-1) + \Delta_{\tilde{r}^f} \times U(0,1) \text{ if } L_j^f(t-1) > \eta_1^f \tilde{L}_j^f(\kappa)
\end{aligned}$$

where $\Delta_{\tilde{r}^f}$ is a fixed increment above or below the previous mark-up, multiplied by a random number drawn from the uniform distribution over the unit interval to make it variable, while η_0^f and η_1^f ($\eta_0^f < \eta_1^f$) are thresholds for the proportion of the loan target that was achieved in the previous period. Essentially, if the bank did not even meet a minimum proportion, η_0^f of its most recent leverage target, it reduces its current ask rate to firms by a random amount which varies between 0 and $\Delta_{\tilde{r}^f}$. If it over-filled its target by a proportion η_1^f, it raises its ask rate in analagous fashion. Note that η_1^f could be greater than unity.

3.8.3. Interbank market spreads

Spreads on interbank market are updated following a similar mechanism with a few differences. First, since rates are offered by interbank borrowers,

[11] Lending on the interbank market will be a residual from unfilled targets on firm lending.

they will go up if the bidder was unsuccessful and down if successful. Second, banks do not set borrowing targets every few periods via an optimisation process; these can adjust every period depending on the bank's intra-day liquidity situation and the bank has no control over them. Third, things are a little more complex as banks have different probabilities of defaults which might be taken into account by lenders, depending on the information available on bank risks. They actually bid in terms of a premium on top of a rate which makes lending (in expectation) equivalent to the risk free central bank deposit facility.

Borrowing banks offer a rate as stated in equation 7, repeated below.

$$r_k^b(t) = \underline{r}_k^\ell(t) + \tilde{r}_k^b((t)$$

where $\tilde{r}_k^b(t) \geq 0$ is a non-negative markup on the lender's reservation rate. This is adjusted each borrowing period as follows. Borrowing banks compare how much they managed to borrow in the last period in which they were borrowers on the interbank period, $t-\tau$, $I_k^b(t-\tau)$, where τ is the number of periods since the most recent borrowing took place, with their target borrowing level $\tilde{I}_k^b(t)$ for the current period and choose the mark-up according to

$$\begin{array}{l} \tilde{r}_k^b(t) = \tilde{r}_k^b(t-\tau) + \Delta_{\tilde{r}^b} \times U(0,1) \;\text{ if }\; I_k^b(t-\tau) < \eta_0^b[\tilde{I}_k^b(t)] \\ \tilde{r}_k^b(t) = \tilde{r}_k^b(t-\tau) \;\text{ if }\; I_k^b(t-\tau) \in (\eta_0^b \tilde{I}_k^b(t-\tau), \eta_1^b \tilde{I}_k^b(t)) \\ \tilde{r}_k^b(t) = \tilde{r}_k^b(t-\tau) - \Delta_{\tilde{r}^b} \times U(0,1) \;\text{ if }\; I_k^b(t-\tau) > \eta_1^b \tilde{I}_k^b(t) \end{array} \tag{12}$$

where $\Delta_{\tilde{r}^b}$ is a fixed increment to the existing rate, made variable in the same manner is was done for firm lending rates. η_0^b and η_1^b ($\eta_0 < \eta_1$) are threshold proportions of fulfilled demand from the last time bank k borrowed on the interbank market (that time is denoted by $t-\tau$. These are similar in interpretation to η^f discussed in the previous sub-section. Note that $r_k^b(t)$ is bounded above by r^H, which is the cost of borrowing from the Central Bank.

4. Simulations

For our simulations we fix the number of banks at 100 as it is roughly in line with the number of banks in several Eurozone economies and allows for a non-trivial interbank market. The central bank lending and borrowing (deposit facility for banks) have rates r^H, r^L which are fixed for each simulation; the latter offers a risk-free return for banks. Banks choose a leverage level (determined by their strategy) $\tilde{\lambda}$ which is a multiple of their equity and this becomes their target to lend to firms. Bank are initialised with a level of equity $\mathcal{E}_j(0)$ and deposits $D_j(0)$.

4.1. Basic Tests

We first consider a simple version of the model in which underlying risk, namely the probability of default by a firm is low ($\rho = 1\%$) in order to see if the model is well behaved.

We start by seeing how the system behaves as the number of firms per bank increases. The number of firms serves as a proxy for the size of the real economy, particularly for the level of demand from the real sector for bank loans. In our model, the real sector is is not explicitly modelled; rather each firm contributes to the banking system in a fixed manner: (i) by creating demand for intermediated funds; (ii) by generating a real return that underpins all financial returns; and most importantly (iii) by introducing risky fundamentals which carry over into the interbank market. Banks are neither inherently productive nor inherently risky; it is the real economy which underpins both these features of the financial system. It is in this sense that firms proxy for the real economy as their profusion creates the possibility for greater reward but also generates the risk that goes with it.

Figure 2 depicts the performance of the system for varying sizes of the real economy. All plots are averaged over 25 runs of 1000 periods each.[12] The underlying model for bank risk is Model B as was described in the previous section.

The left panel of Figure 2 shows how banks allocate funds in terms of both destination and source: loans to firms, loans to each other, reserves held at the Central Bank and loans taken from it. The right panel depicts the interest rates associated with each of these allocations.

The allocations are not surprising: as the number of firms per bank increases, banks lend more to them. Initially they also lend more to each other as the interbank market helps to spread the underlying demand for liquidity across the system. This lending plateaus at some point indicating that after a point, each bank has enough of its own real sector borrowers. At this point banks begin to make use of the Central Bank facility. This leads to a steady increase in the cost of borrowing as the Central Bank facility is the most expensive source of funds and this is passed on as higher interest rates charged

[12] Averaging over a greater number of runs does not qualitatively change the nature of the plots.

to firms. The use of the Central Bank reserve facility steadily diminishes in this process.

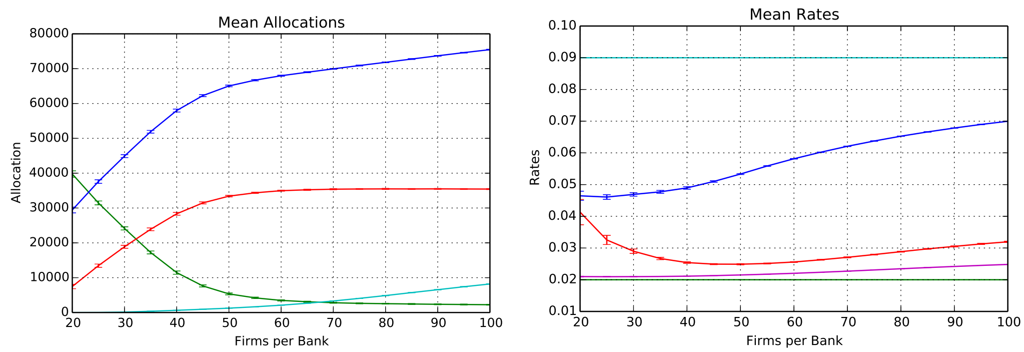

Figure 2: Allocations and interest rates with varying sizes of the real economy: Model B. Firm Lending (Blue), Interbank Lending (Red), Central Bank Reserves (Green), Central Bank Borrowing (Turquoise), Average Cost of Funds (Purple).

An interesting feature of the right-hand plots is that the interbank rate varies non-monotonically with the number of firms.[13] There are two factors at work here: competition amongst banks to lend to each other and the riskiness of interbank loans. With a small number of firms, the number of potential lenders on the interbank market is large relative to borrowers and this by itself tends to reduce the interbank lending rate. At the same time, the banks that lend to firms are more vulnerable to failure and this makes interbank lending itself riskier, pushing up the interbank lending rate.

An explanation for the second effect can be derived from Figure 3, which plots the distribution of banks' direct exposure to firm lending, for three discrete sizes of the real economy: N_F=20; N_F=50 and N_F=100 (these are hereafter referred to as the Low-demand, Medium-demand and High-demand scenarios respectively). In each plot, the horizontal axis measures lending to firms as a multiple of bank equity, while the vertical axis is the distribution of banks at each leverage ratio. In all plots, the maximum leverage ratio is 20. The left hand plot shows the distribution of exposures across all banks while the right-hand plot shows the distribution of exposures for defaulting banks alone.

From the right-hand plots we can see that frequency of defaulting banks tends to rise with their exposure level for all three economies, peaking sharply

[13] A similar shape was observed when the analogous plots were computed for Model D.

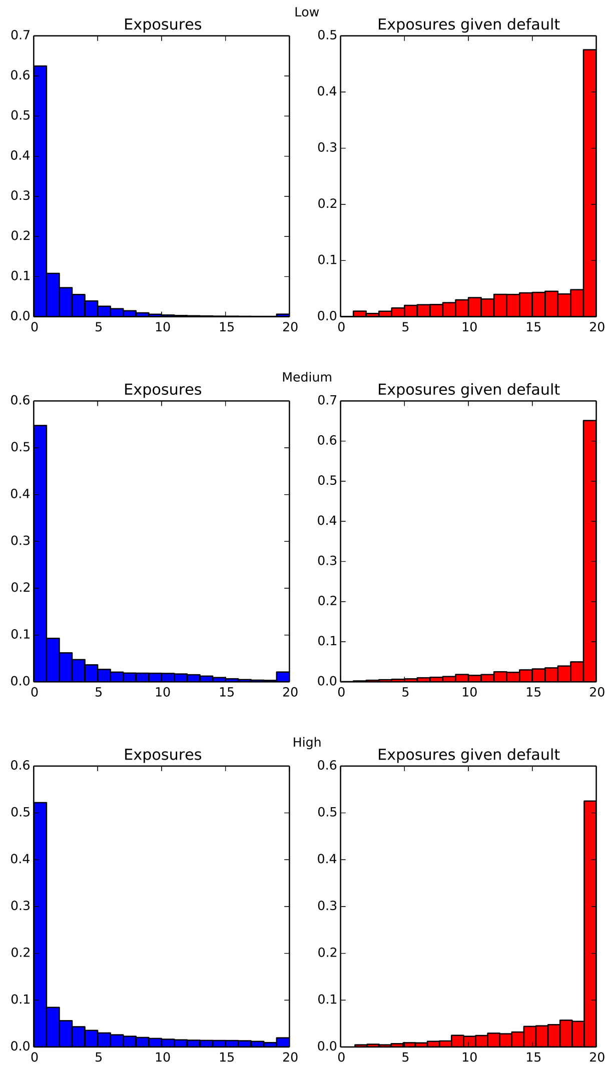

Figure 3: Distributions of banks' exposure to firms: Model B. Low-Demand (Top), Medium-Demand (Middle), High-Demand (Bottom); All Banks (Blue), Defaulting Banks (Red).

at the highest exposure level. This shows the most highly leveraged banks are the ones most likely to default. From the left-hand plots, we see that although the distribution of exposures is quite unequal in all three economies, it is most concentrated in the Low economy: over 60% of banks have no exposure and all but a few of the remaining banks have exposures of less than 5 times equity. Only a miniscule fraction achieve the highest possible exposure. The distribution is more spread out in the Medium and even more in the High economies. Thus in the Low economy only a small number of highly exposed banks monopolise firm lending and these are the banks that end up seeking funds on the interbank market.[14] This makes lending on the interbank market particularly risky and rates reflect this riskiness. When the economy is larger and the distribution of bank exposures is a bit less concentrated the overall risk of default by interbank borrowers also declines.

The above explanation is further supported by Figure 4 which plots the incidence of bank default against the number of firms. It shows that the average rate of bank default is higher in a Low economy than in larger ones.

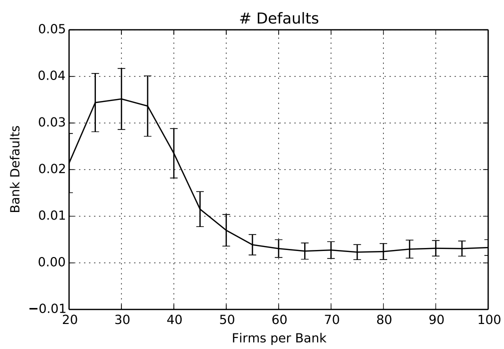

Figure 4: Bank defaults with varying number of firms: Model B.

Eventually, however, as the direct exposure of banks to firms becomes more equal this reduces the pool of available lenders on the interbank market so eventually the competitive effect takes over and this causes the interbank rate to rise again.

Figure 5 compares the baseline behaviour of the economy in a single, 350-period run of the model. Each row of plots compares allocations (left-hand

[14]Each firm always borrows from the cheapest available lender so when the firms are small in number they tend to cluster towards the cheapest banks.

panel) and rates (right-hand panel) over the three discrete sizes of the real economy: Low, Medium and High. In each scenario, the economy tends to fluctuate around a stable steady state, whose properties are consistent with the averages plotted in Figure2. Firm lending increases in absolute terms with the size of the economy, as expected, while interbank lending is lower in absolute terms in the Low economy and about the same in the Medium and Large ones. This is consistent with Figure 2, in which interbank lending plateaus at around $N_F = 50$ (which coincides with the Medium-demand case). Another noteworthy feature of the left-hand plots is that borrowing from the Central Bank is made use of with much greater frequency and in higher amounts in the Medium and High economies than in the Low one. The opposite is true for reserves held at the Central Bank as these fall with the size of the economy. These results are again consistent with Figure 2 in which the use of Central Bank loan facility is on average negligible until $N_F = 40$ and then rises to an average of just under 10,000, while the use of the reserve declines steadily with the number of firms. Both sets of results are explained by the fact when the number of firms increases, there are more lucrative outlets for financial intermediation than holding reserves at the Central Bank so banks leverage themselves even if this means having to make use of Central Bank loan facilities.

A final feature of the left-hand plots is clearest in the Low economy. There is positive co-movement between firm lending and interbank lending negative co-movement between both of those and Central Bank reserves. This is expected: when firm lending faces a downturn banks borrow and lend less amongst themselves and hold on to more reserves.

Turning to the right-hand plots, the steady state values of interest rates appear to be in line with those plotted in Figure 2. One pattern worth discussing is the periodic behaviour of interbank rates in the Low-demand economy. Rather than symmetric fluctuations, these appear to show periodic upward spikes. This pattern is mirrored to some extent by the left-hand plots in the Low-demand scenario: both the blue and the red lines, which measure firm and interbank lending respectively¡ show periodic downward spikes at around the same time as the interbank rate spikes upward.

As an example, consider the Low-economy plots between $T = 10$ and $T = 50$. The interbank rate appears to fluctuate around 3% while loans to firms fluctuate just below 40,000 and interbank loans around 15,000. At approximately $T = 50$, there is a sharp upward spike in the interbank rate paired in the left-hand panel with a drop in firm loans to about 36,000 and

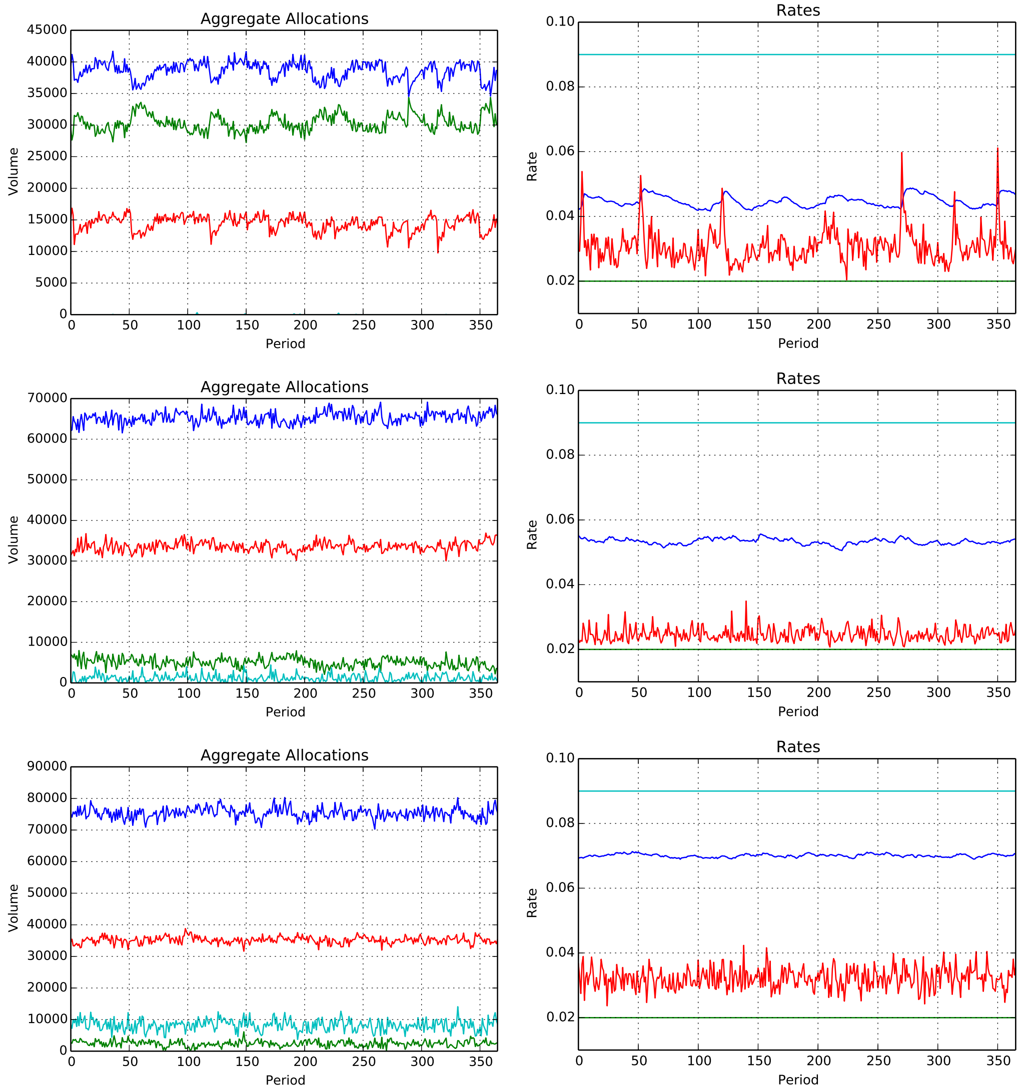

Figure 5: Allocations and interest rates in a single run of 350 periods: Model B. Low=20 (Top), Medium=50 (Centre), High = 100 (Bottom); Firm Lending (Blue), Interbank Lending (Red), Central Bank Reserves (Green), Central Bank Borrowing (Turquoise).

in interbank loans to about 13,000. After a few periods the system goes back to the pattern it had followed before the spike.

Recall that in Low-demand economy, the risk premium plays a bigger role in determining interbank rates than it does in the other two cases; hence it is fair to conjecture that a spike in the interbank rate is caused by a spike in the risk premium on interbank borrowers.

Recall that in Model B, the risk premium is triggered by evidence of financial stress such as an interbank borrower drawing on Central Bank loans or actually defaulting on its loans. (in practice we assessed the risk premium in period t on the basis of borrower behaviour in period $t-1$). Moreover, it is applied by interbank lenders to all interbank borrowers in the near future (in practice we assumed that evidence from period $t-1$ is applied to the risk premium in period t alone).[15] The Low economy is particularly vulnerable to the effects of such evidence, if an when it arises.

Given the small numbers of banks involved in borrowing on the interbank market and the relatively low probability of firm default (1%), there will be a run of periods with no evidence of financial distress inducing lending banks to discount the probability of defaults on the interbank market. But eventually a bank borrower or two will show symptoms of distress, and given that the total number of interbank borrowers is always small, the estimated probability of default by future borrowers will increase sharply.[16] This will then generate the spikes in rates and allocations that we noted in connection with Figure 5. Once the shock has passed, lending rates go down on the interbank market and the economy begins to recover.

In the next set of plots, Figure 6, we see the behaviour of the average allocation of funds and of interest rates in response to changes in the underlying

[15] In an analogous plot for Model D, Low economy, the interbank rate fluctuates much more symmetrically around its mean. Refer to Figure 12.

[16] This conjecture was tested in a simulation for the Low economy in which we simultaneously monitored the paths of interbank rates, default probabilities assigned to borrowing banks and actual defaults by borrowing banks. In these plots there were periods in which default probabilities and actual defaults remained close to zero while the interbank rate fluctuated around a low mean; broken by sudden increases in the default probability as an interbank borrower made use of Central Bank loans; this was immediately followed by a spike in actual interbank rates as lending banks reduced their loan supplies and soon after that a spike in actual defaults as the effect of higher interbank rates precipitated actual defaults. After a while the system wiped this episode out of memory and went back to normal. Details are available.

probability of firm default.

The left panels show allocations and the right ones show interest rates. As expected, higher probabilities of firm default induce less lending to firms, thus less interbank lending and more accumulation of Central Bank reserves.

Interest rates on firm lending rise in line with the greater risk of default in all three economies. The behaviour of interbank rates, however, is surprising in the Low- and High-demand economies. In the Low economy, interbank rates are inverse-U shaped while in the High economy they are U-shaped. Taking into account the direct effects of higher default probability, we would expect that interbank rates should rise monotonically with fundamental risk as happens in the Medium economy. However, as we explained in relation to Figure 2, interbank rates are influenced jointly by the underlying default risk and competition in the supply and demand for interbank funds. With higher probability of firm default, banks that lend to firms inherit some of the riskiness of their clients and this pushes up the price of interbank loans made to them. But higher probability of firm default can also induce banks to switch from direct exposure to firms to lending their surplus funds on the interbank market. All else equal, the latter effect drives down internal rates.

In the Low economy, when the probability of default is low and the proportion of banks that lend to firms is relatively high (given the size of the economy and the fact that very few banks are directly exposed to firms), the first effect dominates while at higher probability of default and less lending to firms the second effect comes to dominate. In the High demand economy, the order is reversed. To understand how the relative weight of the two effects varies in each economy, we need to look at both the allocations and the rates. Consider the High economy first: between $\rho = 0.005$ and $\rho = 0.025$, the interbank rate falls, while on the side of allocations, we see that firm lending is falling while interbank lending is roughly constant. This pattern of allocations suggests that banks are switching funds from the real sector to the interbank market over this interval and this is switch is creating a strong competition effect on interbank rates. After $\rho = 0.025$, firm lending begins to fall at an even faster rate but now interbank lending also falls while Central Bank reserves go up rapidly. These movements suggest that banks are stopping lending in both markets and this in turn is reflected in the rising interbank rates.

The lesson of the above case is that the competition effect dominates when there is a switch in bank lending from the real sector to the interbank market while the pure risk effect dominates when the decrease in lending

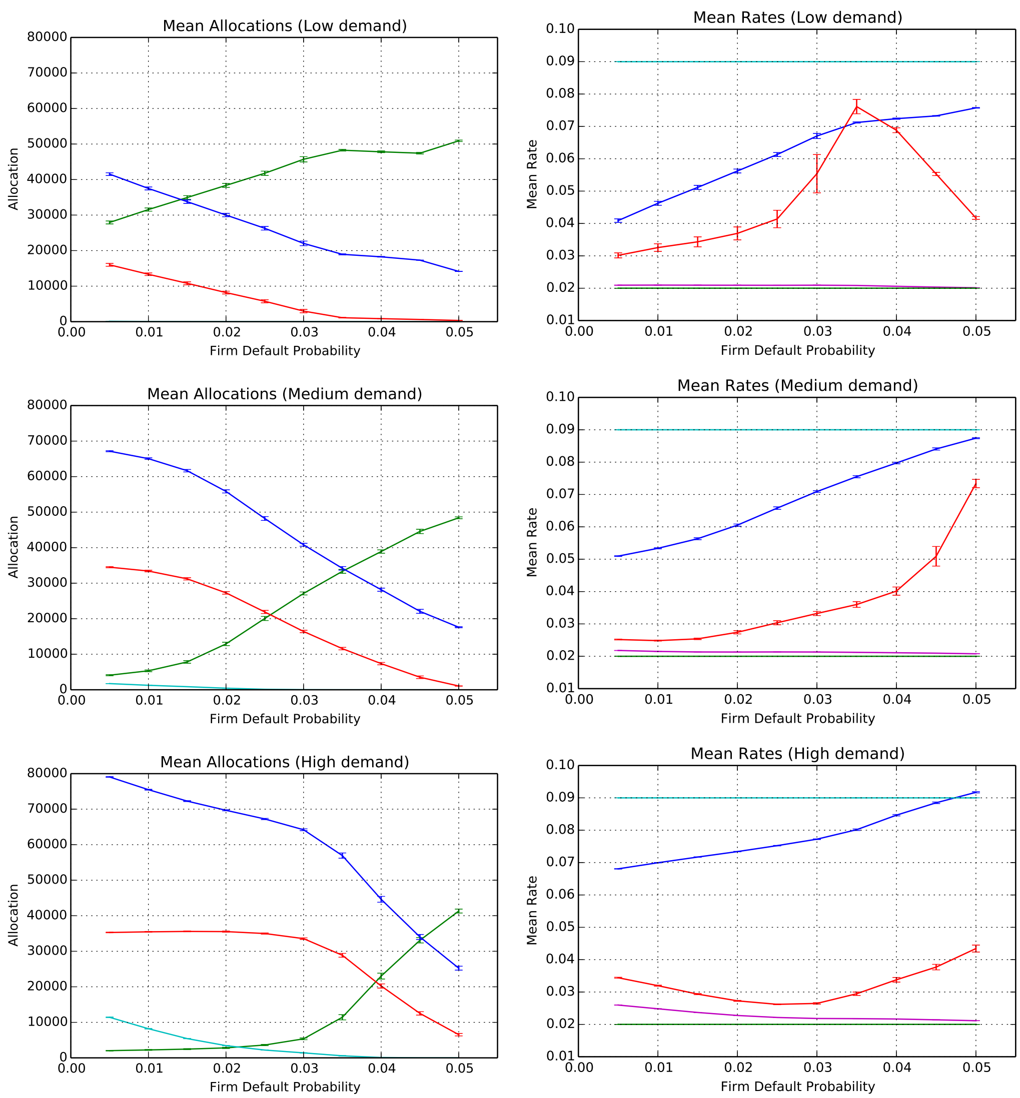

Figure 6: Average allocation and interest rates with varying probability of firm default: Model B. Firm Lending (Blue), Interbank Lending (Red), Central Bank Reserves (Green), Central Bank Borrowing (Turquoise), Average Cost of Funds (Purple).

to firms is matched by a decrease in lending to other banks. If we now look at the Low economy, it is at low default rates that both firm lending and interbank lending move down in approximate parallel (while reserves climb) while at higher default rates, firm lending declines more steeply while interbank lending stabilises, albeit at very low levels. Thus it is at higher default rates that banks appear to be switching from firms to other banks. One explanation for this can be derived from Figure 3 where we noted that in the Low economy at a low default rate of $\rho = 0.01$, only a very small fraction of banks are exposed to firm lending but their exposure levels are very high. Such banks might make their loan offers to firms more restrictive as ρ goes up but they are unlikely to show up as lenders on the interbank market.

Note also that the sensitivity of the interbank rate to firm risk is also higher in the Low-demand economy than in the other two: the slope of the interbank rate line is steep at both ends for this economy. This suggests that counter-party risk is more important at the margin in smaller sized economies than in larger ones. This hypothesis is supported by Figure 4 in which we observed higher default probabilities by banks in the Low economy than in the other two. Further evidence of this will be seen in Figure 8 which maps bank defaults against maximum leverage ratios in each of the three economies.

Finally, a minor observation is that the average cost of bank funds seems to go down with firm default probability, most strikingly so in the High-demand economy. This is somewhat unexpected since a higher default probability by firms implies more fundamental risk for banks and thus an increase in their borrowing costs. But note that this is an average effect brought about by banks' de-leveraging in the face of greater fundamental risk. In particular, in the High-demand economy, banks make use of the more expensive Central Bank facility at low default probabilities of the real sector. As banks de-leverage they draw less and less on these funds and this drives the declining average cost of their own funds. In other words these are *ex-post* costs, driven by de-leveraging.[17]

[17] In any event, this is a theoretical result of the present model in which Central Bank monetary policy is help fixed in the face of various changes in the economic environment that might induce a change in this policy.

5. Regulatory ratios and systemic risk

In this section we carry out a study of the effect of (i) changes in the regulatory leverage ratio and (ii) the degree of connectedness of the interbank market, on bank performance and systemic stability. As stated in the Introduction, this is one the main aims of the present paper. Recall that banks optimise their leverage subject to Central Bank's regulatory constraint.

5.1. Leverage constraints

In Figure 7 we see the consequences on market outcomes of varying the maximum leverage ratio on banks. And in Figure 8 we see the consequences on bank defaults.

The plots show the effect of firm demand on allocation of funds and market rates. In the top-most plot we can see how the demand for credit is quickly met when firm demand is low, so increasing the leverage ceiling beyond 10 has little effect on firm lending or other allocations. The bottom-most plot shows that with High demand the higher leverage levels lead banks to make use of the Central Bank deposit facility. This also leads to a U-shaped relationship between the average cost of funds and the leverage ceiling: at low thresholds, interbank charges are high but decline with leverage as this allows for more lending to other banks and to firms; at high leverage ratios, Central Bank funding for real sector loans is increasingly sought and this pushes up the cost of funds again.

The plots again confirm that for each size of the real economy, firm lending and interbank lending track each other fairly closely while Central Bank deposits move in the opposite direction. Moreover there is a point after which relaxing leverage constraints has little effect on market volumes or prices. In the Low economy, there is little change in mean allocations beyond a ceiling of 10, for the Medium one the levels flatten out after a ratio of 15 and and for the High demand economy, the plateau is reached after 20. Although these results are suggestive they illustrate the possibility that relaxed leverage constraints might not actually induce more lending either to the real sector or to other banks.

Figure 8 (left panel) displays bank defaults as a function of leverage ratios for each of the three economies. In line with Figure 4, banks in the Low demand economy seem to be more vulnerable to failure than in the High demand one, with the Medium one in between.

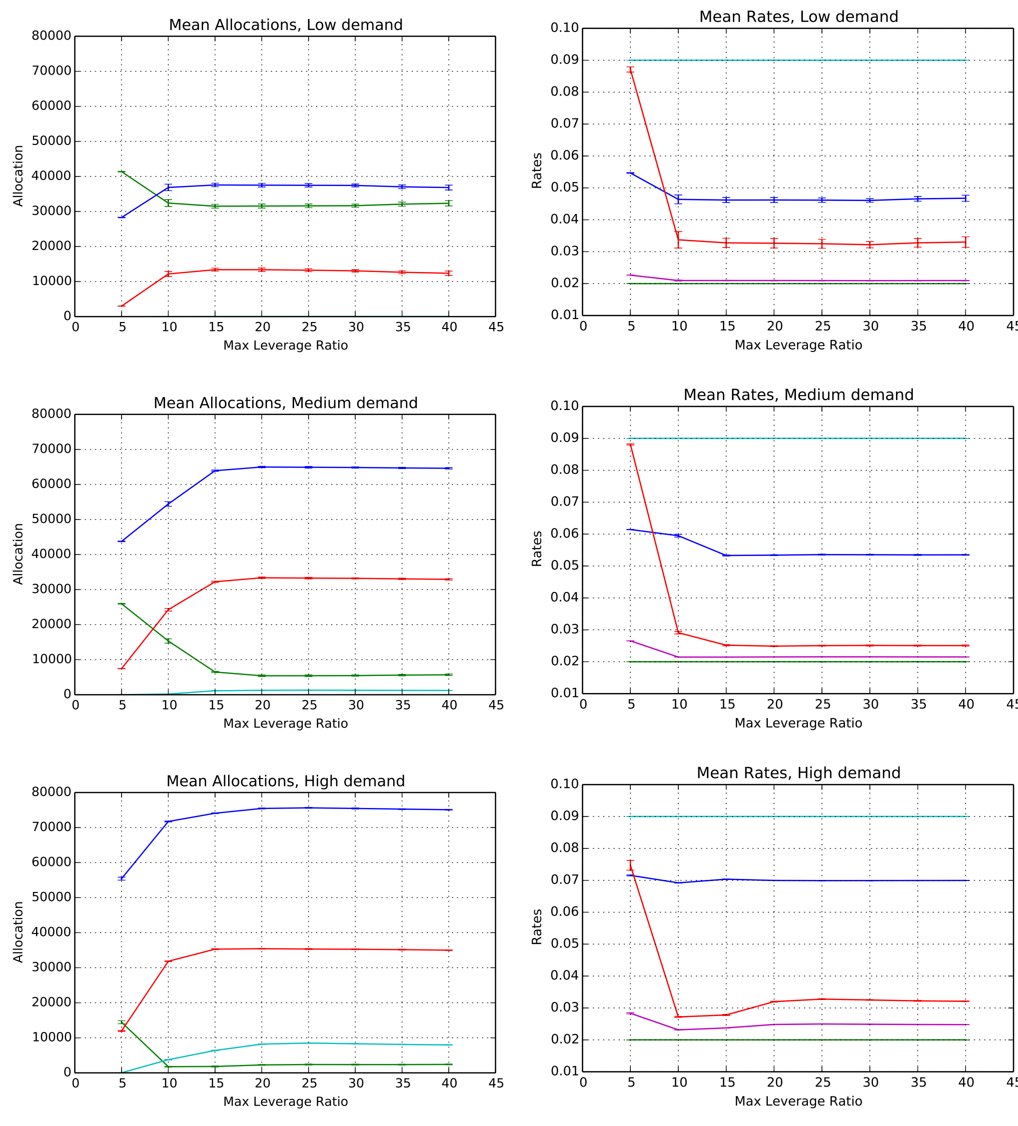

Figure 7: Average allocations and interest rates with varying leverage constraints: Model B. Firm Lending (Blue), Interbank Lending (Red), Central Bank Reserves (Green), Central Bank Borrowing (Turquoise), Average cost of funds (Purple).I

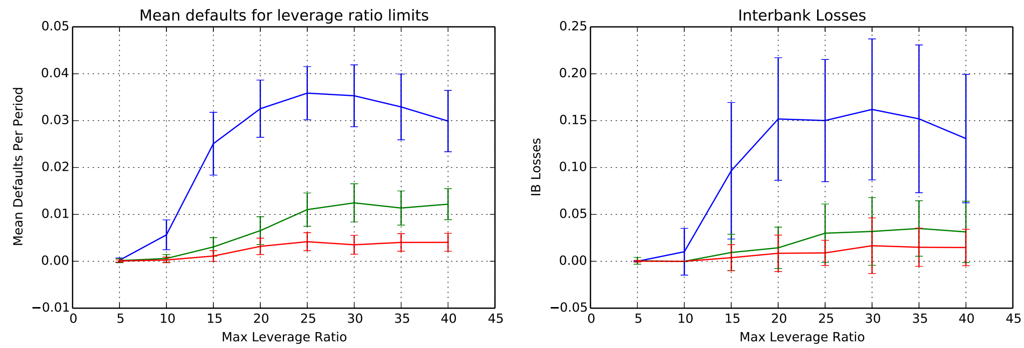

Figure 8: Model B. Mean default per bank (left panel) and Interbank losses (right panel) at varying leverage ratios: Low (Blue), Medium (Green), High (Red).

The gap also grows with the leverage constraint, implying that not only is the low demand economy more vulnerable in absolute terms it is also marginally more susceptible to bank defaults for a given increase in the allowable leverage ratio. Thus, as the ratio increases from 10 to 20, the mean rate of bank failure increases from one every 200 periods to one every 33 periods. Eventually the rate of bank defaults begins to drop. To explore this further we consider the right panel of Figure 8, which shows losses on the interbank market against maximum leverage ratios. The pattern of interbank losses follows closely that of bank defaults in each of the three economies. In the Low economy, after peaking at a leverage ratio of about 30, the rate of interbank losses begins to fall. This may be explained by considering that at given levels of connectivity, higher leverage ratios mean that banks that need funds are able to access them more easily from those banks which they are connected. This helps reduce the concentration of firm loans and spreads risk more evenly.

5.2. Systemic risk

In this sub-section we consider the role of connectivity within the interbank market on contagion and systemic risk. Iori *et. al.* (2006) among others, have shown that increasing interbank connectivity can, depending on circumstances, either enhance the risk-sharing role of the interbank market or make it a source of contagion. We are therefore interested in seeing how changes in interbank connectivity interact with regulatory changes in affecting the market outcomes and stability of the system.

5.2.1. Market outcomes and rates:

Figure 9 depicts market outcomes as functions of connectivity for High-demand scenarios at three different ratios of regulatory leverage: low=10, medium=20, high=40.[18]

We see that a low leverage ceiling leads, after an initial positive effect at very low levels of connectivity, to a negative effect of connectivity on lending in both markets, with Central Bank reserves soaking up the excess funds. For the high ceiling the relationship between firm lending and connectivity slopes upwards, albeit slightly, while that between interbank lending and connectivity becomes flat with Central Bank funding picking up the slack.

An explanation is provided by the plots on market rates. At the low ceiling, due to the high demand for loans from firms, most banks end up filling their order book with loans to the real sector and few banks are left with funds to lend on the interbank market. Increasing connectivity then simply links the banks that do have funds available to lend on the interbank market to a larger number of borrowing banks and this pushes up interbank interest rates, because of stronger competition. Higher funding costs then lead to higher rates on firm loans (notice the upward trends in both rates in the top right plot) and this acts as a dampener on activity in both markets. The implications of this phenomenon for overall economic performance will be discussed below.

Relaxing the leverage ceiling from 10 to 40 allows individual banks to take on more firm lending and also increases the availability of funds on the interbank market. In this case, increasing connectivity beyond a certain level leads to a plateau in allocations across all markets and a gradual decrease in interbank rates. After a connectivity of 0.2, a constant level of firm lending is achieved, which on average means a constant demand for interbank borrowing, so increasing connectivity leads to competitive pressures from the supply side of the interbank market.

[18]For Low- and Medium-demand economies, the higher leverage ceiling do not change outcomes a lot compared to the low ceilings so those cases are also not included.

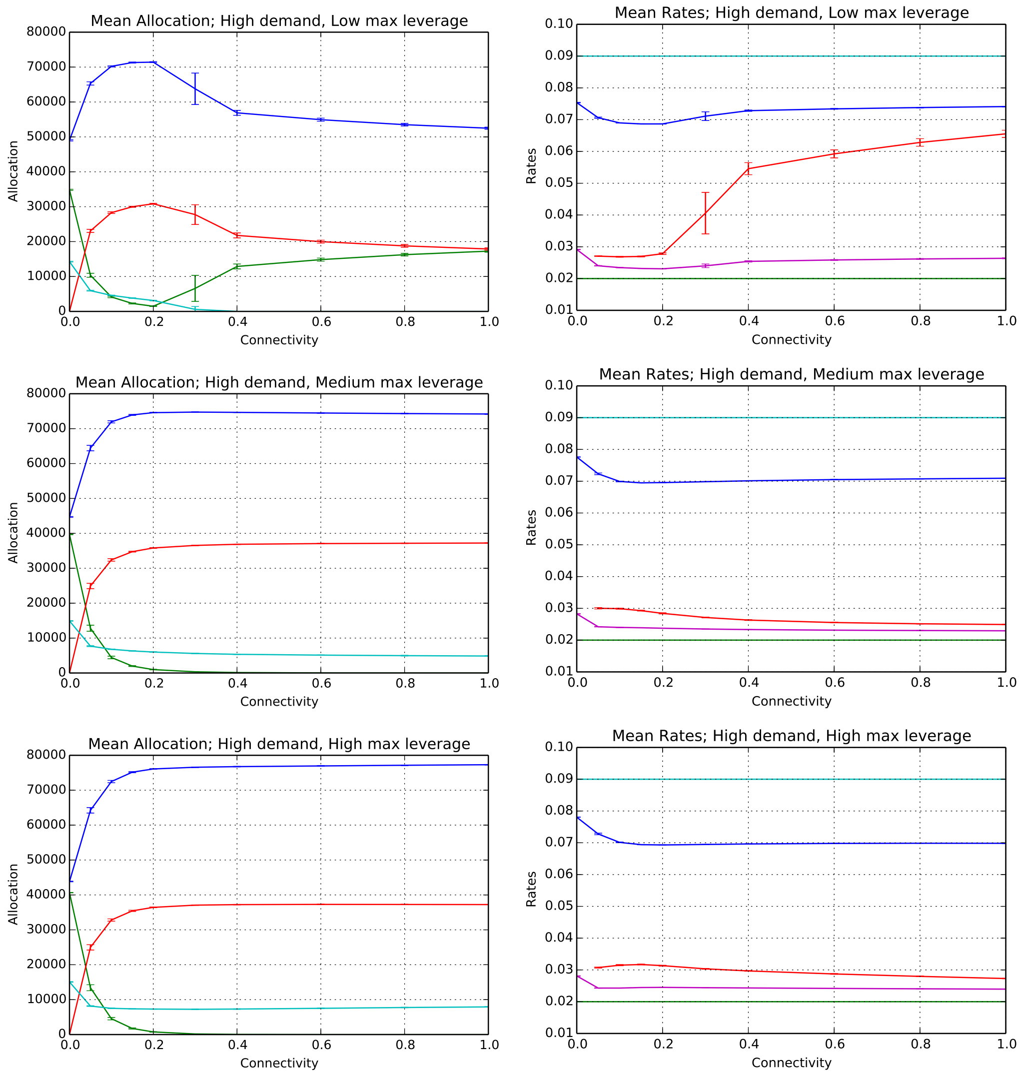

Figure 9: Average allocations and interest rates for varying connectivity: Model B with High demand. Low Max Leverage = 10% (Top), Medium Max Leverage = 20% (Middle), High Max Leverage = 40% (Bottom); Firm Lending (Blue), Interbank Lending (Red), Central Bank Reserves (Green), Central Bank Borrowing (Turquoise), Average Cost of Funds (Purple).

5.3. Systemic stability and profitability:

We use as a measure of systemic stability the rate of bank defaults per unit of funds lent out. Figure 10 depicts these at varying levels of connectivity for the two leverage ratios.

Again, after an upward-sloping phase at very low levels of connectivity, bank defaults go down with increasing connectivity when the leverage ceiling is low. This is true for each size of the economy. When the leverage ratio is high, bank defaults show an increase with increasing connectivity. The case of medium leverage ratios comes in between.

The mechanism underlying these effects can be understood by taking into account results that were already noted in Figure 9 for the case of High demand. In the case of low leverage ceilings increasing connectivity led to a decline in lending to firms after a threshold, for reasons that were explained earlier, while with the high ceiling lending to firms kept increasing, albeit slowly, as connectivity increased. In our model, defaults by firms and the accompanying losses on bank balance sheets are the key source of systemic risk. Given that all loans are of one-period maturity there is no contagion arising from the rollover of debt by distressed banks and since there is no secondary market for firm loans there is no contagion arising from declines in common asset prices. Thus, by allowing greater access to risky firm lending under conditions of high demand and high leverage ceilings, greater connectivity also creates more systemic risk. From the point of view of stability alone, this would be an argument for imposing tighter leverage constraints when demand is high. This is a conjecture that follows from a comparative static exercise; in the next section we shall explicitly consider the dynamic effects of counter-cyclical leverage ratios.

As a function of regulatory leverage ratios, defaults rise in each economy in going from a low ceiling of 10 to a medium ceiling of 20. In going from 20 to the high ceiling of 40, there is not much additional effect.[19]

From the above plots we have seen that in high leverage scenarios, increasing interbank connectivity can promote more bank failures per unit lent and this reduces systemic stability. In this model, greater interbank connectivity reflects a more integrated and frictionless banking system. In this sense, the above effect appears to validate the oft-expressed fear that financial liberalisation promotes instability. At the same time, this effect alone

[19]This will not be the case when we look at Model D in the next section.

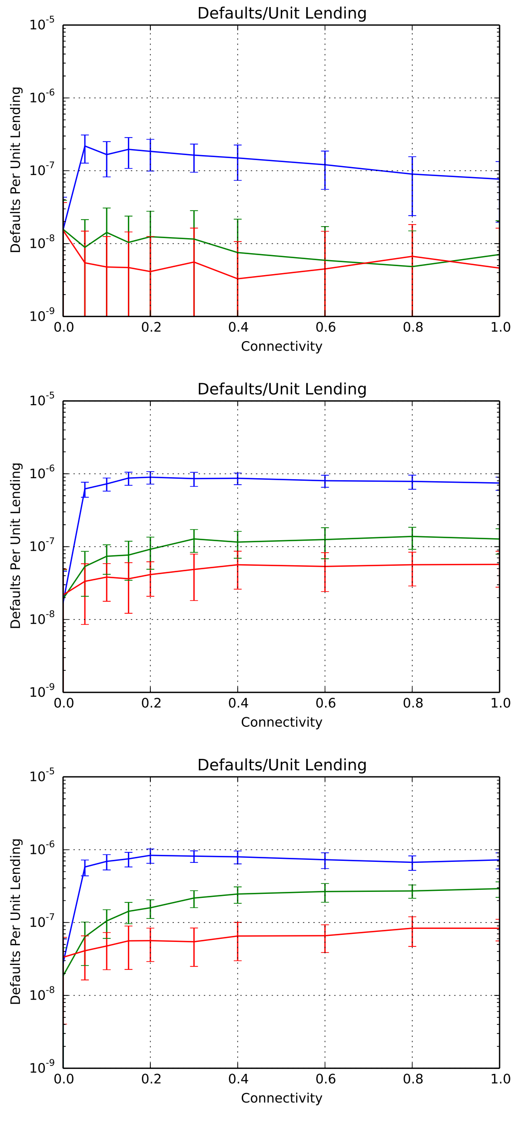

Figure 10: Defaults: Model B. Low Leverage = 10 (Top), Medium Leverage =20 (Middle), High Leverage = 40 (Bottom); Low Demand (Blue), Medium Demand (Green), High Demand (Red).

cannot be used to judge the desirability of financial liberalisation as it has to be balanced against the potential efficiency gain of increased lending to the real sector. In our model, the most natural measure of efficiency is the aggregate profitability of the system. Aggregate profits are the sum of bank profits and firm profits. By allowing firms to undertake productive investment at a cost below its expected return, financial intermediation contributes to firm profits. Banks share in these profits via the rates they charge directly to firms and through the interbank market to each other. Lacking a detailed specification of the household sector in our model, these profits become the measure of economic performance for our paper.

Figure 11 displays the average profits of the banking system at varying levels of connectivity, comparing results across the low, medium and high leverage scenarios.

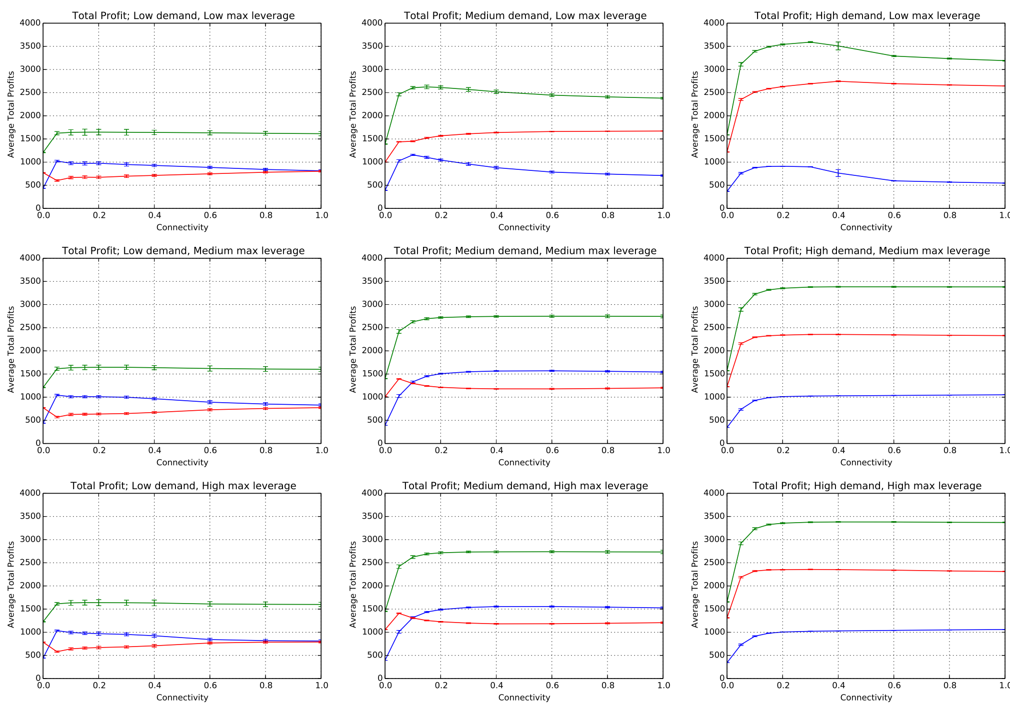

Figure 11: Economy-wide profits at varying levels of connectivity: Model B. Low Demand (Left), Medium Demand (Centre), High Demand (Right); Low Max Leverage = 10% (Top), Medium Max Leverage = 20% (Middle), High Max Leverage = 40% (Bottom); Firms (Blue), Banks (Red), Aggregate (Green).

Some points can be noted. First, an economy with more real sector demand for loans delivers more aggregate profits. Second, more real sector demand for bank loans increases banks' profits and reduces firm profits. Neither of these results are surprising.

Third, lower leverage ratios benefit banks at the expense of firms. Neglecting the Low demand scenario, in which we saw that allocations reach a plateau at the low regulatory threshold of 10, in each of the other demand scenarios, an increase in leverage ratios raises firm profits and lowers bank profits. The explanation for this is that by placing more tightly binding limits on leverage, regulators actually reduce competition among banks for lending to the private sector. This effect is in line with some of the traditional concerns about the anti-competitive effects of regulation and the potential for incumbents to use it for what is known as regulatory capture.

Fourth, given a low leverage constraint, increasing interbank connectivity tends to increase bank profits and lower firm profits, while aggregate profits tend towards an inverse-U shape, especially in the High demand scenario. Focusing on the latter scenario, we have already seen that increasing connectivity under a low leverage ceiling leads after a point to an increase in interbank and firm rates and this discourages firm loans, which form the basis of all profits. Thus aggregate profits decline. The lesson is that under the wrong circumstances, in this case very tight regulatory regimes, promoting competition amongst banks can actually discourage lending to the real sector. When the regulatory regime is more relaxed, *i.e.* at the high leverage ratio, this effect disappears. At the same time, note that after 0.2 connectivity, aggregate profits tend to flatten out, while in Figure 10 bank failures continue to rise with connectivity. This suggests that in this particular scenario, at least, the greater instability of financial liberalisation is not justified in higher performance.

Finally, allowing banks to leverage themselves more has ambiguous effects on aggregate profits. In Low demand economies (the left-hand column plots), increasing leverage does not have much effect on any of the profits. Moreover, moving from medium to high leverage produces no change in any of the three economies; indeed the medium leverage case is included in the plots only for the sake of comparison with the alternate model for assessing bank risk.

In the Medium-demand case, going from a low to medium leverage ceiling leads to higher profits after a threshold connectivity of 0.2. In the High-demand case: up to a connectivity level of 0.5, aggregate profits are higher at the low leverage ratio than at the medium or high one. Beyond that the order reverses, albeit very slightly. Recall that in the High-demand case with low leverage, we have already seen that greater interbank connectivity increases interest rates which reduces firm lending, and this tends to lower aggregate profitability in the economy as a whole. At the same time, in the same scenario greater connectivity also reduces costly bank failures and this effect increases aggregate profitability. In the low leverage case, we see that at low connectivity levels, the positive effects of a small increase in connectivity via reduced bankruptcies outweighs its negative effects via less firm lending. This pushes up aggregate profits above those in the higher-leverage scenarios. However, as connectivity rises, the additional effect of high interest rates in the low leverage case kicks in and this eventually outweighs the stabilising effects of low leverage and high connectivity.

6. Regulatory experiments:

We now turn to the effects of two regulatory reforms that have come to prominence in recent years. The first is for stricter compliance by banks of Pillar 3 of the Basel 2 framework, which calls for transparency and disclosure of information to market participants for evaluating the riskiness of bank portfolios. The second is for leverage ratios that change counter-cyclically with the business.

6.1. The disclosure model:

We consider a model in which banks portfolios are common knowledge to market participants. We call this the Disclosure model, or model D.

We start by verifying one of the observations that was made about the Low-demand economy in Figure 5 of Model B. In that case, the time path of allocations and interest rates periodically spiked *upwards*. Figure 12 depicts an analogous time path for Model D. In keeping with expectation, the fluctuations appear to be much more symmetric around the mean. As claimed in our explanation of Figure 5, the upward spikes in Model B arise because, when market participant lack information about the individual riskiness of bank assets, a credit crunch arises affecting all banks whenever a few highly leveraged bank borrowers develop symptoms of distress. Greater transparency about individual bank risks can mitigate this possibility.

Figure 13 compares allocations and rates across low, medium and high regulatory regimes in the High-demand economy.[20]

[20] The medium leverage case shows enough difference with respect to the other two scenarios in Model D that we have decided to include it in all plots.

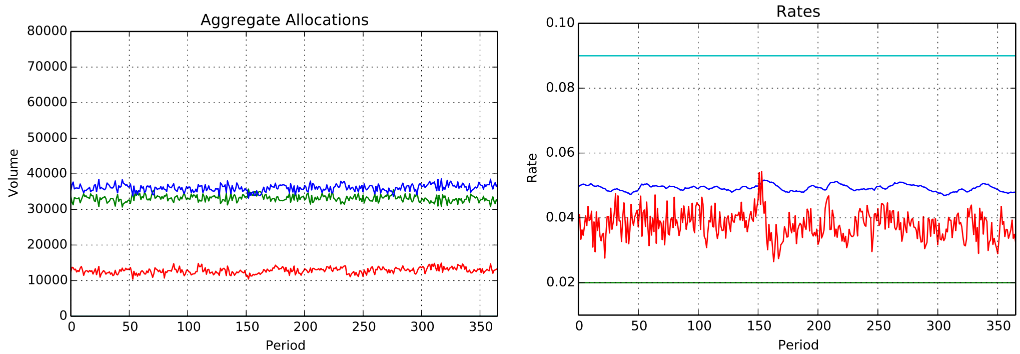

Figure 12: Allocations and interest rates in a single run: Model D with Low demand

The effect of increasing connectivity on allocations and rates is approximately the same as it was in Model B. One difference is that both allocations and rates change more smoothly as functions of connectivity than they did in Model B. An implication of the smoother change is that at low levels of connectivity interest rates are higher and loan volumes are lower than they were in Model B. The allocations reflect the rates, which in turn reflect the more precise information that is available to lenders in assessing individual borrower risk. This counter-acts the competitive pressure which led to lower interbank rates at low connectivity in Model B.

Another difference is in the behaviour of interbank rates in the high leverage scenario. While interbank rates fall as a function of connectivity in both Model B and Model D, the decrease is more rapid in Model D. Thus at higher connectivity levels, the interbank rate is lower in the latter model than in the former. The volume appears approximately the same. Although small, this difference must reflect the greater precision of information held by lender banks in Model D. The discussion of the next set of plots will shed further light on why more precise information helps lower average interbank borrowing rates.

Figure 14 depicts plots defaults per unit of lending and is analogous to Figure 10 which applied to the benchmark model.

The effect of connectivity on bank defaults is similar to Model B, with two differences . First, defaults in the Low-demand rise as the leverage ceiling is raised from 10 to 20 but then decrease, albeit by a small amount, as it is further raised to 40. In Model B, defaults were non-decreasing in regulatory ceilings for the same Low-demand economy (see Figure 10.

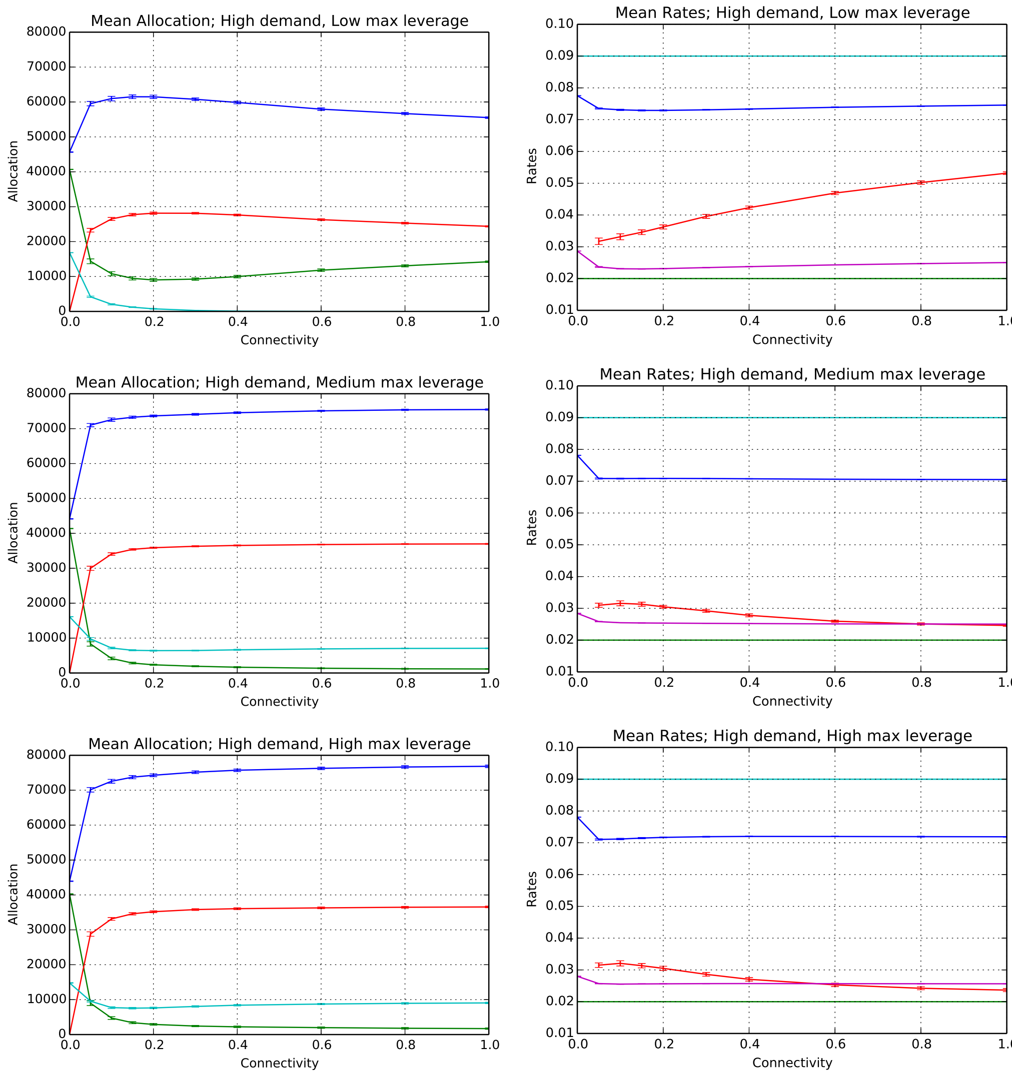

Figure 13: Average allocations and interest rates for varying connectivity: Model D with High demand. Low Max Leverage = 10% (Top), Medium Max Leverage = 20% (Middle), High Max Leverage = 40% (Bottom), Firm Lending (Blue), Interbank Lending (Red), Central Bank Reserves (Green), Central Bank Borrowing (Turquoise), Average Cost of Funds (Purple).

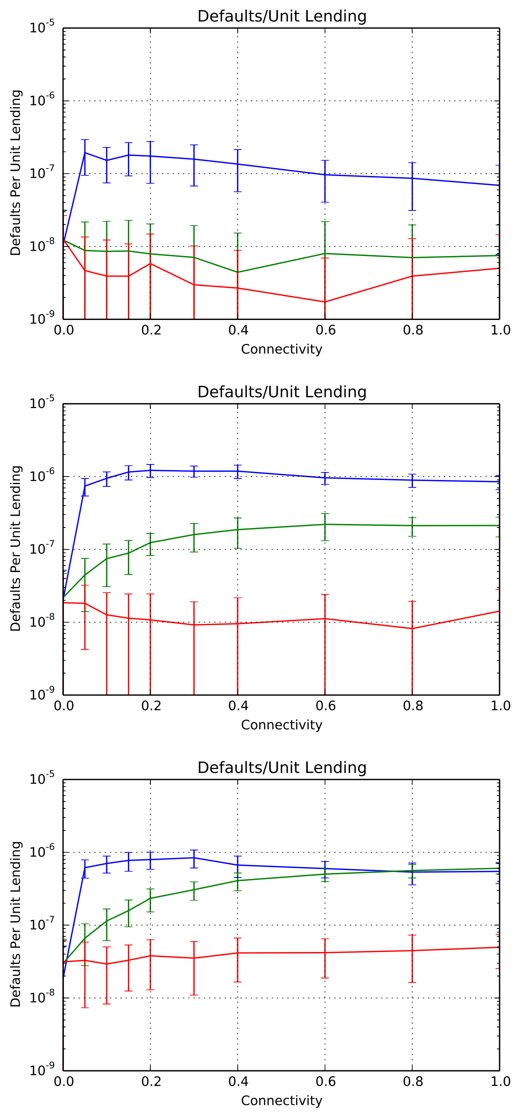

Figure 14: Defaults per unit of lending: Model D. Low Leverage = 10 (Top), Medium Leverage = 20 (Middle), High Max Leverage = 40 (Bottom); Low Demand (Blue), Medium Demand (Green), High Demand (Red).

Second, at high levels of connectivity in the High-demand economy and the high leverage ratio, the rate of bank failures appears slightly lower in Model D than in Model B, This is consistent with the behaviour of interbank rates in this scenario. Given that lending banks have better information on interbank borrowers, riskier borrowers will be charged higher interest rates and all else equal, will post higher lending rates to firms, which will in turn make them less likely to be selected by firms. In equilibrium safer borrowers will be selected and the interbank rate will accordingly reflect this. Greater connectivity thus enhances the potential for the interbank market to select safer borrowers and this leads to commensurately lower inter bank rates.

At the same time, for the same High-demand, high leverage ratio case, there is a noticeable difference in the rate of defaults under medium and high leverage ceilings: it is approximately half an order of magnitude higher under the latter ceiling than under the former. This was not the case with Model B and can help explain the differences in aggregate profitability in the two models.

Figure 15 plots bank, firm and aggregate profits as functions of connectivity for each demand scenario at low, medium and high leverage ratios The plots appear to be similar with Model B with two noteworthy differences,both of which relate to the High-demand economy. . The first concerns firm profits (and thus aggregate profits) in the top-most (low leverage) plot of the High-demand economy. These change more smoothly with increasing connectivity in Model D than they did in Model B. This is in keeping with the smoother dependence of interest rates and allocations on connectivity, which was explained in the discussion of Figure 13.

The second is that in Model D, aggregate profits for the High economy are greater under the medium leverage ceiling than under the high one. This appears to be because of the significant increase in the rate of bank failures in going from medium to high leverage ratios, which was not the case in Model B. Given the trade off between liquidity and stability, aggregate profitability need not increase monotonically with leverage ratios

6.2. Dynamic Leverage Ratios

We now consider the effects of dynamically varying leverage ratios, returning to the framework of Model B. We do so in two steps: first, we move away from the discrete scenarios of Low, Medium and High demand, exogenously introducing time variation in the number of firms as a proxy for fluctuations in demand for loans from the real sector to the banking sector.

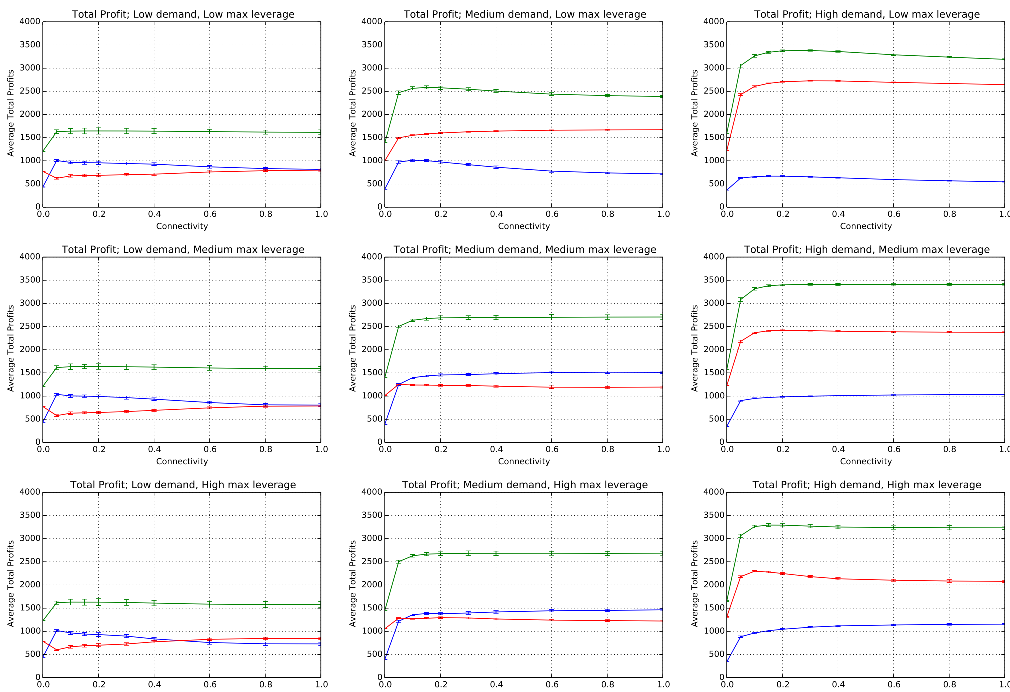

Figure 15: (Economy-wide profits at varying levels of connectivity: Model D. Low Demand (Left), Medium Demand (Centre), High Demand (Right); Low Max Leverage = 10% (Top), Medium Max Leverage = 20% (Middle), High Max Leverage = 40% (Bottom); Firms (Blue), Banks (Red), Aggregate (Green).

We chose the amplitude of variations along with other parameter values in order to mimic the allocations that were previously obtained under the static cases of Low and High demand. A sample path is displayed in Figure 16. As expected, firm lending, interbank lending and Central Bank borrowing move pro-cyclically while Central Bank reserves move counter-cyclically. The plots on interest rates reflect the movements in allocations.

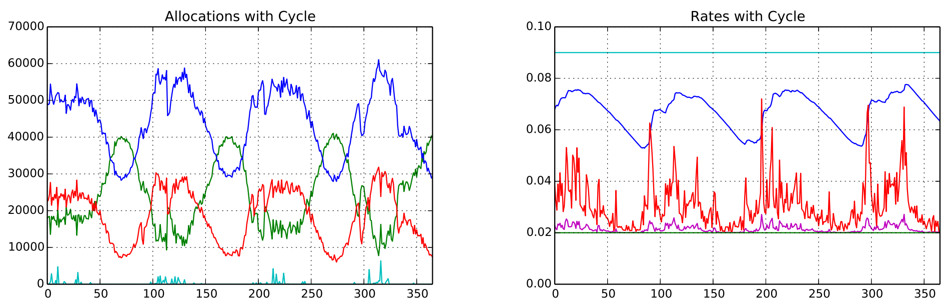

Figure 16: Allocations and interest rates with an exogenous macroeconomic cycle: Model B. Firm Lending (Blue), Interbank Lending (Red), Central Bank Reserves (Green), Central Bank Borrowing (Turquoise), Average Cost of Funds (Purple)

Next, we simulated the economy under two alternative scenarios: first a scenario in which regulatory leverage ratios are adjusted counter-cyclically, rising in a recession and tightening in a boom, and second, one in which they are adjusted pro-cyclically.[21] The first case reflects the widespread belief that banks should be allowed greater flexibility to lend in times of recession, funded by additional capital buffers that have been accumulated in times of boom. The second case reflects what might happen if regulators panic and impose tighter controls on banks and markets just when a crisis hits.

Figure 17 compares average allocations and bank defaults per unit of

[21] Strictly speaking, our method of adjusting leverage ratios differs from a literal application of the Basel 3 rules. The latter require adjustments to depend on the credit gap, which is the difference between the credit-to-GDP ratio and its long-term trend. In our model, by contrast, the adjustment is made on the basis of the volume of firm lending, a proxy for real economic activity and thus for our purposes a proxy for GDP itself, rather than on its ratio to a measure of financial activity. This is because, unlike the real world where stock markets and retained earnings can be used to finance the real sector, in our model all real activity requires bank credit. In addition, some economists, *e.g.* Repullo and Saurino (2011), Edge and Meisenzahl (2011), have criticised the credit-gap measure as vulnerable to strengthening rather than reducing pro-cyclicality in regulatory ratios.

lending under the contrasting dynamic policy regimes of fixed leverage ratios, counter-cyclical ratios and pro-cyclical ratios. The point labeled 0 along the horizontal axis represents a constant leverage ratio (the medium regulatory ratio of 20 is the baseline case). The positive values to the right represent counter-cyclical adjustments around the baseline ratio. Higher numbers indicate a higher speed of adjustment; thus 2 implies that whenever an economy experiences a recession, the leverage ratio is increased by 2 units (reduced by 2 if it experiences a boom); 4 means that it is increased by 4 units and so on, up to a possible maximum of 40. Negative numbers to the left of 0 represent analogous pro-cyclical adjustments.

From the right-hand plots, it can be seen that counter-cyclical policies do indeed reduce the mean rate of bank defaults over the business cycle although the stabilising effect of a faster speed of adjustment in the leverage ratio seems to diminish in going from 2 to 4. Pro-cyclical ratios tend to increase bank defaults, although in this case the effect of speed of adjustment appears to be non-monotonic.

These results are consistent with the expectation that an appropriately designed regime of counter-cyclical leverage ratios can prevent credit crunches in bad times while preventing systemically unsustainable levels of lending in good ones. At the same time, from the left-hand plots we see that the added stability comes at the expense of average volumes in both the interbank and the firm lending markets. Compared to the fixed leverage ratio, counter-cyclical ratios tend to reduce both types of lending while pro-cyclical ones seem to have no effect on volumes.

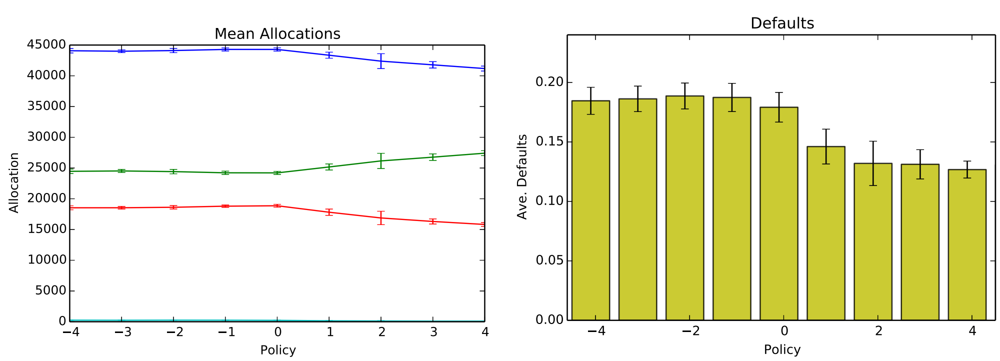

Figure 17: The effect of variable leverage ratios on allocations and bank defaults: Model B. Firm lending (Blue), Interbank Lending (Red), Central Bank Reserves (Green), Central Bank Borrowing (Turquoise).

One reason why counter-cyclical ratios tend to lower average turnover in loan markets was already noted in the discussion of Figure 7. We saw that in periods of low demand, allocations flatten out at a low leverage ratio. This suggests that the bite of regulatory constraints will be asymmetric between a boom and a recession; in a boom the lower constraint is likely to bind and reduce activity while in a recession, allowing the constraint to rise is likely not to have an impact on allocations.

7. Conclusions

We developed a model of a banking system connected to a simplified real economy consisting of a productive firm sector with both banks and firms optimising their behaviour on credit markets. We also explored the impact of proposed reforms to reduce the probability of bank default and reduce contagion within the financial system.

We found that both the contribution of banks to the performance of the real sector and the stability of the credit system depend on market demand as well as on regulatory constraints. While bank lending to the real sector tends to be non-decreasing in both market demand and regulatory ceilings, stability was found to have a less clear-cut relationship with both factors. In addition, the degree of interbank connectivity has ambiguous effects on both economic performance and the possibility of systemic failure, depending again on market demand and regulatory constraints.

We found that loan pricing depends not only on demand but also on the leverage ratio ceiling. In Medium-demand economies relaxing the leverage ratio from 5% to 15% can lead to a significant decline in firm lending rates and an increase in firm lending but in a Low-demand economy, a similar relaxation has hardly any impact on either.

The effectiveness of regulatory measures in improving financial stability was found to depend on the level of credit demand. In particular, in a Low-demand economy the regulatory ceiling affects bank defaults in a non-monotonic way: first increasing and then decreasing as a function of the leverage ceiling.

We used the model to estimate the impact of leverage constraints on aggregate profitability, a proxy measure of economic performance: in the benchmark model which was based on incomplete information, aggregate profitability was non-decreasing in the leverage ratio at all three demand scenarios and at all levels of connectivity. By contrast, in the model based on disclosure of bank risks, aggregate profitability increased when the leverage ratio increased from low to medium but then it decreased when the leverage ratio was fixed at the high.

We further tested the impact of changes in the leverage ratio by introducing an exogenous cycle that started in the real sector and studied the impact of dynamically varying leverage ratios on both lending activity and bank stability.

Our simulations confirmed the beneficial impact of a counter-cyclical ratio on bank stability but at the same time, the average level of lending to firms falls over the business cycle. The effect of a lower leverage ceiling during a boom is not offset by that of a higher ceiling in recessions. This was consistent with our comparative static results which showed that in low-demand economies, lending levels are rather insensitive to increases in the leverage ratio.

These conclusions strengthen the suspicion that regulating the banking system with a mixed structural and prudential model exacerbates the trade-off between the stability and the average efficiency of financial intermediaries. Maximising both desirable objectives seems unattainable and regulators should think in terms of a framework which maximises one of the two subject to acceptable constraints on the other.

At the same time we acknowledge that our model describes an economy without either an in-built tendency for endogenous business cycles or all the sources of financial contagion that might apply in the real world. The source of contagion in our model is direct exposure to counter-party credit risk, exacerbated in one model by a lack of information on individual default risk in interbank borrowing. Because the structure of loans in both firm and interbank credit markets is very short-term, plus the fact that Central Bank lending is always available at a constant interest rate, there is no liquidity risk (an important target of the new Basel 3 rules). There is also no fire sale effect in our model.

Planned extensions include allowing firm loans to have long maturities, in which case a bank that suffers a firm default, will need to reduce its leverage which, given the difficulty of rapidly liquidating firm loans, will then put pressure on its ability to lend on the interbank market in later periods. This will induce a propagation mechanism via liquidity hoarding on the interbank market. Extending the model further, by allowing secondary markets for firm debt can also generate a fire sale effect. Of course, a complete analysis of systemic risk requires endogenising both the financial crisis and the business cycle, which is the ultimate goal of the CRISIS project.

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Appendix A. Configuration of Model

Appendix A.1. Parameters

Below we present the main model parameters with their default values used for the results presented above.

- *Target update frequency*, how frequently leverage target is updated. Default: every period.
- *Number of firms per bank*. Default: 25/50/100 for "Low"/"Medium"/"High" demand.
- *Mean firm loan demand size*. Default: 20.
- *Number of banks each firm approaches*. Default: 5.
- *Connectivity*, how likely it is for any two banks to be connected on interbank market. Default: 0.2.
- r_H, Central Bank Lending Rate. Default: 0.09
- r_L, Central Bank Lending Rate. Default: 0.02
- T^g, *Number of periods after borrowing from the Central Bank a bank is denied an inter bank loan* Default: 1
- T^h, *Period over which banks default are observed* Default: 1
- *Probability of firm loan default*. Default: 0.01.
- *Number of Banks*. Default: 100.
- *Initial deposit*. Default: 500.
- *Initial equity*. Default: 100.
- *Deposit volatility*, weight for proportion of deposits withdrawn and allocated to another bank (in proportion to equity). Default: 0.1.

The adjustment thresholds below were selected because they seemed to work reasonably well. There qualitative results seemed to be unaffected by their precise level. A lower threshold was selected for the interbank market to account for its higher period to period volatility.

- $\eta_0^l = 0.8$
- $\eta_1^l = 0.9$
- $\eta_0^b = 0.5$
- $\eta_1^b = 0.9$